



**OPERATIONAL PLANNING OF CHANNEL AIRLIFT MISSIONS USING
FORECASTED DEMAND**

THESIS

Taylor J. Leonard, Captain, USAF

AFIT-ENS-13-M-09

**DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY**

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

DISTRIBUTION STATEMENT A
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED

The views expressed in this thesis are those of the author and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the United States Government. This material is declared a work of the U.S. Government and is not subject to copyright protection in the United States.

AFIT-ENS-13-M-09

**OPERATIONAL PLANNING OF CHANNEL AIRLIFT MISSIONS USING
FORECASTED DEMAND**

THESIS

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the
Degree of Master of Science in Operations Analysis

Taylor J. Leonard, BS

Captain, USAF

March 2013

DISTRIBUTION STATEMENT A
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED

**OPERATIONAL PLANNING OF CHANNEL AIRLIFT MISSIONS USING
FORECASTED DEMAND**

Taylor J. Leonard, BS
Captain, USAF

Approved:

Jeffery D. Weir, Ph.D. (Chairman)

Date

Raymond R. Hill, Ph.D. (Member)

Date

Abstract

Past research proposed that it is possible to forecast cargo demand using time series models and that there exists potential cost savings in the way that Civilian Reserve Air Fleet (CRAF) is used for cargo airlift. United States Transportation Command (USTRANSCOM) performs annual "fixed-buys" of CRAF to support airlift needs. Forecasted cargo demand would allow for reasonably accurate cargo projections vs. the current expected value estimation. Accurate forecasting allows for greater "fixed-buys," further incentivizing CRAF airlines as well as reducing the number of additional aircraft purchases during the quarterly and monthly buys. Multiple forecasting models are constructed and the results compared. A Monte Carlo simulation using a discrete pallet destinations distribution and a discrete pallet port arrival date distribution (based on historical data) outputs a month of projected pallet weights (with date and destination) that are equivalent to the forecasted cargo amount. The simulated pallets are then used in a heuristic cargo loading algorithm. The loading algorithm places cargo onto available aircraft (based on real schedules) given the date and the destination and outputs statistics based on the aircraft ton and pallet utilization as well as number of aircraft types used and the total cost of the projected airlift schedule. A technical approach to the operational planning of cargo airlift could provide significant cost savings or could provide an alternative planning approach changing the future of USTRANSCOM operations.

Dedicated to my wife and our wonderful children

Acknowledgments

I would like to express my sincere appreciation to my faculty advisor, Dr. Jeffery Weir, for his guidance and support throughout the course of this thesis effort. The insight and experience was certainly appreciated. Most importantly, thank you to my beautiful wife and children for their support during this effort.

Taylor J. Leonard, Capt

TABLE OF CONTENTS

	Page
Abstract.....	iv
Acknowledgments.....	v
List of Figures	ix
List of Tables	xi
List of Equations	xii
Operational Planning of Channel Airlift Missions Using Forecasted Demand.....	1
I. Introduction.....	1
Background.....	1
Problem Statement.....	5
Objectives	5
Hypothesis	6
Assumptions	6
Limitations	7
Implications	8
II. Literature Review	9
CRAF Program	9
Forecasting Techniques	11
Forecasting Demand	22
Summary.....	25
III. Methodology	26

	Page
Scope and Data Description.....	26
Model Selection	28
Modeling Approach	36
Model Inputs	38
Cargo Loading Algorithm.....	39
System Output	41
Model Verification & Validation.....	42
Summary	43
IV. Analysis.....	44
Model Analysis	44
Real Pallet Scenario	46
Redistributed Scenario	49
Times Series Model Scenarios.....	50
Full Schedule Scenario	53
All Organic Scenario	55
Results.....	56
Summary	58
V. Conclusion.....	60
Results.....	60
Research Conclusion	61
Recommendations.....	63

	Page
Future Research	63
Works Cited	65
Appendices.....	69
Appendix A.....	69
Appendix B	70
Appendix C	74
Appendix D.....	77
Appendix E	79
Appendix F.....	86
Appendix G.....	87
Vita.....	88

List of Figures

Figure 1 Aircraft Payload during Peacetime Planning (Air Mobility Planning Factor, 2011)	7
Figure 2 JMP Raw Data Plot of Cargo	15
Figure 3 JMP Plot of Transformed Cargo Data	15
Figure 4 JMP Output of the ACF and PACF for the Cargo Demand	16
Figure 5 First Difference Transformation	17
Figure 6 Theoretical ARIMA (1,1,1) Model	17
Figure 7 Estimated ARIMA(1,1,1) Model for Cargo (tons)	17
Figure 8 RACF and RPACF for ARIMA(1,1,1) Cargo Model	18
Figure 9 ARIMA(1,1,1) Model Summary	20
Figure 10 ARIMA(1,1,1) Parameter Estimates	20
Figure 11 AMC Mission Character Codes (AMC/A3CF, 2012)	27
Figure 12 JMP Output - Model Selection Criteria	28
Figure 13 Tons of Cargo vs. Regression Models	32
Figure 14 Tons of Cargo vs. Exponential Smoothing Models	33
Figure 15 Tons of Cargo vs. ARIMA Models	33
Figure 16 Tons of Cargo vs. Transfer Function Models	34
Figure 17 Cargo Loading Algorithm	40
Figure 18 Actual Schedule Simulation (Cargo)	47
Figure 19 Actual Schedule Simulation (Pallets)	47
Figure 20 Redistributed Simulation (Cargo)	50
Figure 21 Redistributed Simulation (Pallets)	50
Figure 22 Redistributed Simulation (Missions Flown)	50

Figure 23 Forecasted Cargo Demand	52
Figure 24 Forecast Simulation (Mission Flown)	52
Figure 25 Full Simulation (Cargo).....	55
Figure 26 Full Simulation (Pallets).....	55
Figure 27 Full Simulation (Missions Flown).....	55
Figure 28 Organic Simulation (Cargo)	56
Figure 29 Organic Simulation (Pallets)	56
Figure 30 Organic Simulation (Missions Flown)	56
Figure 31 Monthly Forecast Model Graphs.....	70

List of Tables

Table 1 Definition of ARIMA Parameters.....	17
Table 2 Model Number Designators.....	29
Table 3 Actual Tons of Cargo vs. Predicted Tons of Cargo.....	31
Table 4 Percentage Deviation from Actual Tons of Cargo.....	31
Table 5 Quarterly Buy Forecast Comparison	35
Table 6 Monthly Buy Forecast Comparison.....	36
Table 7 Sample Simulation Output.....	41
Table 8 Example of Simulation Results with Actual Pallet Data	43
Table 9 Percentage Deviation Iterative Model Comparison.....	45
Table 10 One Month Ahead Forecast Accuracy and Average	46
Table 11 Intervention Model Simulation - Pallet Statistics “Oct-11”	53
Table 12 Full Daily Schedule	54
Table 13 Scenario Summary - Total Airlift Missions.....	57
Table 14 Scenario Comparison of Cost Savings.....	58
Table 15 All Model Residual and Percentage Deviations	75
Table 16 Monte Carlo Simulation Construction.....	77

List of Equations

Equation 1 Mean Square Error	19
Equation 2 R^2	19
Equation 3 AIC	19
Equation 4 SIC	19
Equation 5 MAPE	20
Equation 6 MAE	20

OPERATIONAL PLANNING OF CHANNEL AIRLIFT MISSIONS USING FORECASTED DEMAND

I. Introduction

Background

The United States Transportation Command (USTRANSCOM) is located at Scott Air Force Base, IL and is the single manager of the U.S. global defense transportation system (DTS). USTRANSCOM is composed of three component commands, the Army's Military Surface Deployment and Distribution Command, the Navy's Military Sealift Command, and the Air Force's Air Mobility Command (AMC) (USTRANSCOM History, 2012). AMC is also located at Scott AFB and provides aerial refueling, medical evacuation, passenger transportation, and cargo delivery anywhere around the world. AMC's passenger transportation and cargo delivery capabilities are supported by the Civil Reserve Air Fleet (CRAF) program which allows the Department of Defense (DOD) to contract aircraft from civilian airlines to meet national objectives. One of the more important aspects of the CRAF program is its ability to provide additional commercial airlift aircraft in times of national emergencies.

Within AMC is the 618th Tanker Airlift Control Center (TACC) which is responsible for planning, scheduling, and directing more than 1,300 mobility aircraft for a number of operations to include strategic airlift. The 618th TACC includes the Global Channel Operations Directorate (XOG) which manages worldwide strategic airlift operations and employs military aircraft such as the C-5 Galaxy and the C-17 Globemaster III, along with civilian aircraft to fulfill airlift requirements (618th Tanker Airlift Control Center, 2008).

AMC and TACC are responsible for organizing U.S. tanker, airlift, and inter-theater aeromedical evacuation capabilities worldwide. Airlift during the Global War on Terror

(GWOT) has significantly evolved since Desert Storm, causing a direct increase in the demand on the available air assets. Airlift historically supports forces from behind rather than acting as a frontline operation (Second Line of Defense, 2011). However, with altered deployments, airlift has received much more forward pressure than ever before. Within in the last ten years, a heavy commitment to Central Command to airlift all of the necessary equipment, machinery, weaponry, and rations to the deployed troops has become the norm. Unfortunately, there are not enough organic aircraft available to airlift everything that is needed. A crucial element of TACC has become its ability to leverage commercial assets or CRAF. CRAF is utilized for channel missions or regularly scheduled flights that fly fixed routes on a predetermined schedule. The CRAF schedule is generated from USTRANSCOM airlift requirements based on historical data. As of now, there is no mathematical projection of the airlift needs for the future (Second Line of Defense, 2011). The number of organic aircraft that are used for airlift is dependent on the number that are not dedicated to other missions and that are in good condition to fly. These organic aircraft are then used for either military missions or to carry outsized cargo that cannot fit in a civilian aircraft. TACC then augments the organic forces with the civilian contract charters. As of 2011, 80% of airlift needs were met by commercial carriers (Second Line of Defense, 2011).

Initially born during World War II, CRAF was officially created by executive order in 1951. The creation allowed for the nation to have a contingency plan to meet airlift requirements in times of need (emergencies or wartime) when airlift exceeded the capabilities of military aircraft fleet (Knight & Bolkcom, 2008). The current relationship between the military and the civilian airline industry was made official in 1987 by President Ronald Reagan's National Airlift Policy. The policy stated that in order to protect national security interests in a wartime

environment, the military and the civilian airlift would be interdependent in meeting wartime airlift requirements. An important feature of the CRAF program is that it is still voluntary for airlines to participate. Fortunately for the U.S. military, the incentive program is strong enough to maintain a relationship with 32 airlines (Michael W. Grismer, 2011).

Although CRAF has proven itself invaluable to the military's airlift needs, the fact remains that the program is very expensive (Michael W. Grismer, 2011). The expense is necessary for the most part, but with the current economic crisis and the need to cut costs, the CRAF program presents an area where large savings are feasible. The key to achieving cost savings is a more technical approach to the planning that already occurs when purchasing civilian aircraft for our future airlift needs.

To bring the cost of CRAF into perspective, since September 11, 2001 (9/11) the Department of Defense (DoD) exceeds \$3 billion per year in CRAF costs when the DOD only allocates \$2.5 billion each year for the CRAF program (House of Representative Hearing, 111 Congress, 2009). While this allocation is an enormous amount of money, the cost for the military to build up and maintain the same number and capacity of aircraft over the life of the program in inflation-adjusted dollars is possibly \$128 billion (House of Representative Hearing, 111 Congress, 2009). A new 747-8 costs approximately \$180 million for one plane and while we reserve many different sized aircraft, we still request approximately 1100 civilian aircraft a year (House of Representative Hearing, 111 Congress, 2009). It is quite easy to imagine how the costs add up if the DOD were to replicate the necessary inventory number as organic military aircraft and provide all of the additional support necessary.

There do not seem to be any documents that firmly state what the cost of a particular type of civilian aircraft is to fly for the CRAF program. For this study, previous estimates from past

studies will be used (Lindstrom, 2012). The Boeing 747 is one of the most common CRAF aircraft, and the estimated cost of contracted airlift from Dover AFB to Bagram, Afghanistan is \$460,000. Let us say that there are two 747s contracted to fly on the same day to the same location, but there is only enough cargo to fill one plane. The options are to fly both planes regardless if one is full or not, or to fly one and cancel the second. Many people would probably think if a plane is already purchased, then why would one want to cancel it? This is the school of thought that TACC has adopted and applies in their methodology. The issue is it is cheaper to cancel an aircraft than to fly it. To think of the cancellation cost as a scheduling fee provides a different perspective to the example. The DOD has paid \$100,000 per 747 to secure the aircraft to fly a military mission on that day of the month and will pay an additional \$360,000 to actually fly the aircraft on the scheduled day. The DOD will pay \$200,000 total, but will only pay the additional cost \$720,000 if both aircraft are flown. If one flight is cancelled, then both reservations fees are still paid, but there is only one \$360,000 payment ($\$100,000 + \$100,000 + \$360,000 = \$560,000$). The \$560,000 is significantly less than the full \$920,000.

A new planning methodology suggesting that flights be cancelled if a minimum cargo weight is not met would contribute to cost savings. Often times, the main goal is to shorten port hold times, or the time until cargo departs the base. Cancelling flights may cause some port hold times to increase since the cargo would wait until enough cargo arrived for the plane to meet the minimum weight requirement. This study will show that the port hold times will not be significantly affected and cargo will still depart in a timely manner. The identification of the issue with cancellations and the possible savings involved led to a number of studies, in turn providing the foundation for this thesis. This led to pointing out the main problem, finding a methodology to predict the amount of cargo that will be freighted. The annual buy is based on

the predicted amount of freight tonnage. If this amount can accurately be projected for a full year, it may resolve over-scheduling or under-scheduling contracts. Since intermediate buys are then completed quarterly and monthly, the unknown surges of cargo will also be included in short term forecasts.

Problem Statement

Cargo demand changes frequently and rapidly in a wartime environment. It is very difficult to specify twelve months in advance the number of aircraft one would need to airlift a hypothetical number of cargo tons. Cargo demand is dependent on a number of factors such as the timeframe of the war, the set up of the forward operating bases, and whether or not U.S. troops are surging. Current demand is the expected value from previous years (Second Line of Defense, 2011). If planners are able to forecast demand then it is also possible to simulate and optimize the number of commercial and organic assets needed to lift the cargo and provide a rough schedule as well.

An additional problem is the cost of flying unnecessary aircraft. The cost of cancelling a CRAF is significantly less than the cost of flying the aircraft, meaning it is possible to save money just by cancelling the flight. If cancellations are viewed as sunk reservation costs, unrelated to the additional cost of flying, then it is easier to envision cost savings by flying the least amount of aircraft as possible. Most savings are still generated by the benefit of accurate predictions and only scheduling what is actually needed.

Objectives

The primary objective is to examine the effect of advanced mathematical modeling on the operational planning and scheduling of CRAF aircraft. The effects, on both cost and schedule, of

optimizing the number of the aircraft available will be quantified and analyzed in a number of scenarios providing a detailed look at the solution.

Hypothesis

The hypothesis of this research is two-fold. First, current estimates of cargo demand for future years demand are only moderately effective and an advanced mathematical model would provide more accurate upfront purchase numbers and less underutilized CRAF purchases.

Second, a simulation that optimizes and provides an overall average for the allocation of the cargo demand and the optimal airframe needs can realize further gains in the accuracy of the purchase and ensure that airlift is being used to the DOD's and military's advantage.

Assumptions

There are not many assumptions necessary in moving forward with solutions for this problem. The problem is handled in a way to provide an analysis of alternatives to the decision maker and to include sensitivity analysis as well in order to cover as many uncertainties as possible in the problem. The main assumption to be addressed comes when using Boots on the Ground (BOG) as an input in the forecasting models. All forecasts are based off of 98,000 troops being present each month in Afghanistan for all of FY11. This estimate is provided by congressional estimates for the Global War on Terror (Belasco, 2011).

The simulation uses peacetime aircraft load planning factors to replicate real world planning. CRAF is currently inactive and planning occurs at peacetime requirements so the allowable cabin loads (ACLs) are set to a lower value (Mobility, 2012). The aircraft are capable of carrying greater capacities, but those allowances are to be considered in wartime environment. Figure 1 provides a quick look at the assumed ACLs and number of pallet positions available on

the organic and civilian transport aircraft. These parameters are the basis of the simulation and any comparison statistics that occur later on.

Aircraft Type	Pallet Positions	Cargo (Stons)		Passengers ^{4,6}		Standard NEO Passengers
		ACL ²	Planning ³	ACL	Planning	
C-130	6	17	12	90	80	92/74 ⁵
C-130J	8	22	18	145	128	128
C-17	18	65	45	101	90	101
C-5	36	89	61	73	51	73
KC-10 (Airlift)	23	60	32	75	68	75
KC-135 (Airlift)	6	18	13	53	46	53
A-330	-	-	-	-	240	266
B-747	33	120	104	296	296	347
B-757	13	38	33	115	115	175
B-767	26	67	56	190	190	220
B-777	27	114	99	246	246	260
DC-8	18	40	31	-	-	-
DC-10-30	30	88	77	287	287	314
MD-11	35	98	85	329	329	355

Figure 1 Aircraft Payload During Peacetime Planning (Air Mobility Planning Factor, 2011)

Limitations

This research is limited to the specified Area of Responsibility (AOR) of Afghanistan since U.S. forces have been withdrawn from Iraq. Further limiting the analysis is the focus on Dover AFB, DE. There are other ports that operate in the same nature, but the large majority of cargo shipments to the AOR depart from Dover AFB due to its location on the East Coast as well as its primary mission being large scale airlift.

There are limitations in any forecast due to the type of information used and the type of problem. With this problem, only monthly data is being considered due to having limited information on additional inputs. The monthly data is only available starting in 2005 through 2011, which limits the potential data points to 81 observations. 12 of these points are withheld

for validation further reducing the series to 69 observations. This is a feasible set of data points, but it may have been easier to work with a larger data set.

The last limitation is the original data set, or the Global Air Transportation Execution System (GATES) data that is used for the problem. It is possible that the parsing process to be described in Chapter 3 does not include all available information. This is due to limited knowledge and experience with aircraft mission codes and pallet IDs.

Implications

Planning ahead is always beneficial, but in this case, planning ahead can reduce the cost of the CRAF program to the DOD. This study will show that there are more accurate ways to predict cargo demand that are still easily implemented. The benefit of accurate predictions at each purchase stage is tremendous. There are abundant cost savings by scheduling aircraft to fit the actual demand versus scheduling aircraft based on historical averages. The analysis in Chapter 4 will show that it is possible to reduce the number of planes flown in a month and better utilize the planes provided to provide significant cost savings when compared to planning methods in the past.

II. Literature Review

This chapter discusses the usefulness of CRAF so the reader can gain an understanding of what the program provides and why airlift schedules currently exist as they are. There is also a discussion of forecasting techniques and how they are selected and forecasting with air cargo demand. Using forms of regression and time series modeling is not foreign to the Department of Defense (DOD) or the United States Air Force (USAF). There have been multiple research papers written regarding military demand and airlift forecasting in a wartime environment, but there do not seem to be any papers or articles presented in popular literature about the combined topics. The literature review presented below, provides a brief overview of the main topics and the combined application will be presented in later chapters.

CRAF Program

As highlighted earlier, in order to meet wartime needs, the DOD supplements its organic military aircraft with commercial carriers through the CRAF program. The great benefit of the CRAF program and one of the main reasons why it is still so prevalent in today's wartime environment is that it minimizes the cost to the government by guaranteeing aircraft availability during a surge without the added cost of maintaining organic capabilities. A general understanding of the program and its benefits and drawbacks may be necessary to derive further value from this study. The DOD spends billions of dollars annually to make substantial use of participating carriers. Participating carriers must make their aircraft and aircrews available on short notice, with some of the suddenness mitigated through two different types of business purchases known as a "fixed buy" and an "expansion buy." The "fixed buy" requires that the DOD submit/prepay for a percentage of their airlift services upfront for the coming year, thus signing a one-year contract. All additional requirements or additional airlift services are

purchased at multiple points within the year during an “expansion buy.” The “fixed buy” is guaranteed payment a year in advance and therefore was a strong incentive for CRAF partners to continue participating in the program. The benefit of the “fixed buy” for the DOD is to ensure that routine missions to transport people and cargo to overseas stations are already accounted for (Arthur, 2007).

Since the beginning of the wars in Iraq and Afghanistan, the fixed buy has averaged about 20 percent of CRAF business. It was foreseen that “expansion buys” would increase due to deployments closer to areas of operation. What was not predicted were the large increases in the cargo being airlifted overseas and how the DOD could have decreased the “expansion buys” by looking forward. In 2007, it was proposed that the DOD provide more guaranteed buys based on expected requirements (Arthur, 2007).

A common question that has arisen throughout the years is “Why doesn’t the military purchase their own aircraft?” The CRAF program is by no means free; the DOD pays rates based on weighted average carrier costs. This minimal cost was approximately \$1.5 billion a year during Desert Storm and is much greater now. The cost to the Air Force to acquire and support the number of additional aircraft adequate for a major crisis, including aircrews, and maintenance, at that time, would have been anywhere from \$15 to \$50 billion. It could be argued that the DOD has or will soon pay the same amount out of pocket already, but the costs to the Air Force would constantly grow due to continued support of the aircraft, as well as upgrade costs or aircraft replacement costs (Knight & Bolcom, 2008). Under that realization, the use of CRAF by the DOD is easily justified, and the focus has been on how to revamp the incentives to the carrier participants to keep them involved in the program.

In current CRAF operations, excesses in the CRAF capacity numbers have been identified as a possible risk by the Government Accountability Office's evaluation of the DOD's Mobility Capabilities and Requirement Study 2016 (Borseth, et al., 2010). By reviewing and analyzing past schedules and the amount of cargo airlifted, this claim is easily verified and was identified as a portion of the problem statement in Chapter 1. The CRAF program is critical to the DOD's cargo airlift capability as well as its ability to meet our national objectives (Solis, et al., 2009). It is important to better manage such an important capability effectively to reduce wasteful spending on behalf of the government as well as to reduce the cost implications on the airlines themselves for near term scheduling.

Forecasting Techniques

There are numerous regression and forecasting techniques available to apply to nearly any scenario with data. Below are descriptions of the techniques that are applicable to this study.

Simple linear regression assumes that there is a relationship between the dependent variable (Cargo) and the independent variable (BOG) that can be approximated by a straight line. Quadratic and polynomial regression is a form of nonlinear modeling that incorporates the equation of a simple parabola or a more complex curve with the coefficients or slopes of the independent variables representing the rate of curvature of the shape or the trend. Time series regression is a form of polynomial regression that uses time as the independent variable (Bowerman, O'Connell, & Koehler, 2005).

Smoothing models include simple moving average, exponential smoothing, and Holt-Winter's Method. Exponential smoothing is a method that accounts for changing trends and seasonal factors over time. More recent observations are given more weight compared to older observations. Exponential smoothing has additional variations of the broader technique to

account for strong trends in seasonality, such as Brown's Method or Damped Trend Method. For this research Holt-Winter's Method (Additive), Seasonal Exponential Smoothing, and Simple Exponential Smoothing were the three best smoothing models. Smoothing models applied to cargo forecasting was completed in recent research efforts, allowing for this research to focus more advanced techniques (DeYoung, 2012).

Box-Jenkins Models, more commonly known as Auto-Regressive Integrated Moving Average (ARIMA) models, are forecasting models that are used to describe stationary time series in terms of relationship between data and the forecast errors. A time series is stationary if the mean and the variance of the series are constant through time. If not, the series is considered to be nonstationary and must be transformed. An autoregressive (AR) model refers to a model that expresses the current time series value as a function of past time series values. A moving average (MA) model refers to a model that uses past random shock values (errors) to predict the current time series. A random shock value is the difference between the actual value and the forecasted value better known as the residual and it describes the effect of any remaining factors outside of the time series on the model (Bowerman, O'Connell, & Koehler, 2005). An AR and an MA model can be combined to create a mixed model where all components are represented. The "I," or integrated, component represents whether or not a difference transformation is used on the data series. A first difference of the time series values is equivalent to the current time series value at time t minus the previous time series value at time $t-1$. This transformation is applied to the entire data series to create a new working series (Bowerman, O'Connell, & Koehler, 2005). Differencing transformations can be applied to both the nonseasonal and the seasonal components of the data series to create an updated "working" series.

The ARIMA model is represented in the format $ARIMA(p,d,q)$, where p represent the order the AR term, d represents the order the differencing term and q represent the order of the MA term. A time series that includes seasonal factors can be modeled in a more advanced form to include additional ARIMA terms purely related to the seasonal occurrence of the data (every 12 months for example).

An advanced ARIMA model allows for an independent time series to be used to predict a dependent time series. There are two popular methods to perform this, the first is simpler and is known as an intervention model. Intervention models are normally used when some kind of extreme event occurs such as a natural disaster that may impact the values of the data set such as a production capacity (Bowerman, O'Connell, & Koehler, 2005). In this case, there is no extreme event, but there is still an external event, BOG, that may or may not affect the variable to be forecast, or cargo. The result is to estimate a linear regression model that describes the intervention (BOG) and then, while assuming the error terms are statistically independent, develop an ARIMA model that adequately describes the error terms. The ARIMA model of the error terms can be substituted for the error term at the end of a general regression model.

The second form is more advanced and is known as a transfer function model and predicts future values of a time series on the basis of past values of one or more related time series. It is similar to a regression model, but now includes a serially dependent response, inputs, and error terms. The same modeling method applied to single time series ARIMA models is applied to the transfer function method, but is an iterative process used on multiple time series. Combining forecasts to improve prediction performance is also applied to multiple transfer function model as well as to a transfer function and other single time series ARIMA models. (Bowerman, O'Connell, & Koehler, 2005) The combined forecasts method allows for linear

combination of the two forecasts from at least two different methods to be created. The forecasts of two methods can be combined to create a single superior forecast than either model alone. (Montgomery, Jennings, & Kulahci, 2008). The three forms of ARIMA modeling described above, standard ARIMA, intervention models and transfer functions are all modeling forms applied and compared with the exponential smoothing methods in this research. The comparison and analysis of the techniques begins in Chapter 3.

ARIMA model building is a three-step iterative procedure that first requires a tentative model to be formed through analysis of the historical data. Secondly, the unknown parameters are estimated and lastly, residual analysis determines model adequacy and room for improvements (Montgomery, Jennings, & Kulahci, 2008). This brief outline of the procedure may make the process seem quick and insignificant, which at times may be the case, however, a much more detailed discussion on all three steps is required to actually apply the iterative technique correctly. Only the steps of the procedures that are directly applicable to the model development will be quickly explained below.

Estimating an ARIMA model requires an initial evaluation of the raw data to determine if the data set is stationary or has constant variance. As seen in the left hand plot (Figure 2) of the cargo data there is nonconstant variance displayed by the large differences between the increases and decreases in the data points and by the increasing mean, both hinting that a first-difference is necessary. A first-difference transformation is applied and the data set (Figure 3) is significantly altered and now stationary.

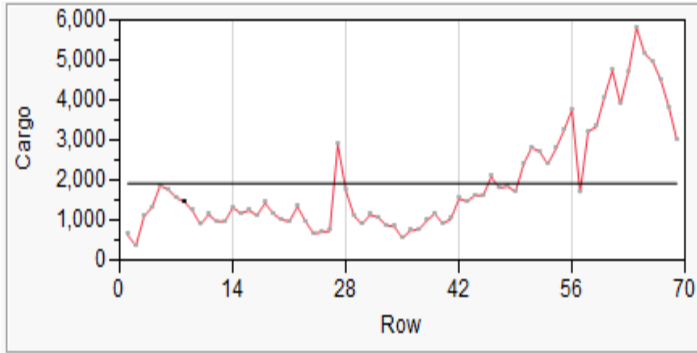


Figure 2 JMP Raw Data Plot of Cargo

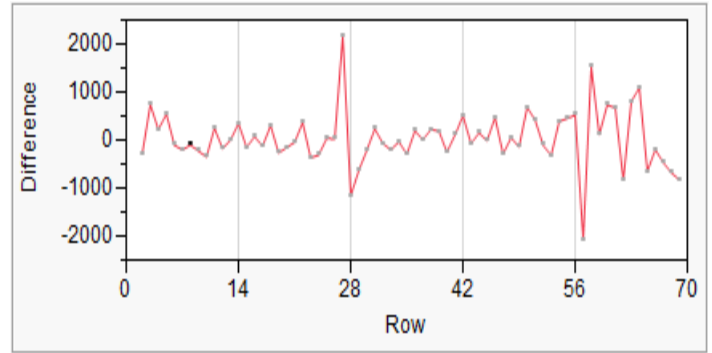


Figure 3 JMP Plot of Transformed Cargo Data

Once the data is stationary, the Auto Correlation Functions (ACF) and Partial Auto Correlation Functions (PACF) are reviewed for lags of significance and to determine the manner in which the consecutive lags decrease. These indicators describe the parameters and the type of model (ex. AR or MA) that best fits the data. Significance in the lags represents the presence of autocorrelation between the time series data points. Looking at the ACF, the left hand function in Figure 4 below, a significant spike at the first lag means that we are rejecting the null hypothesis that the autocorrelation is equal to zero. The function also displays a dying down trend. The PACF, the right hand function in Figure 4, shows one near significant spike and a slow dying down trend. Dying down on both the ACF and the PACF represents a mixed parameter model with the number of parameters corresponding to the number of significant spikes in the ACF and the PACF.

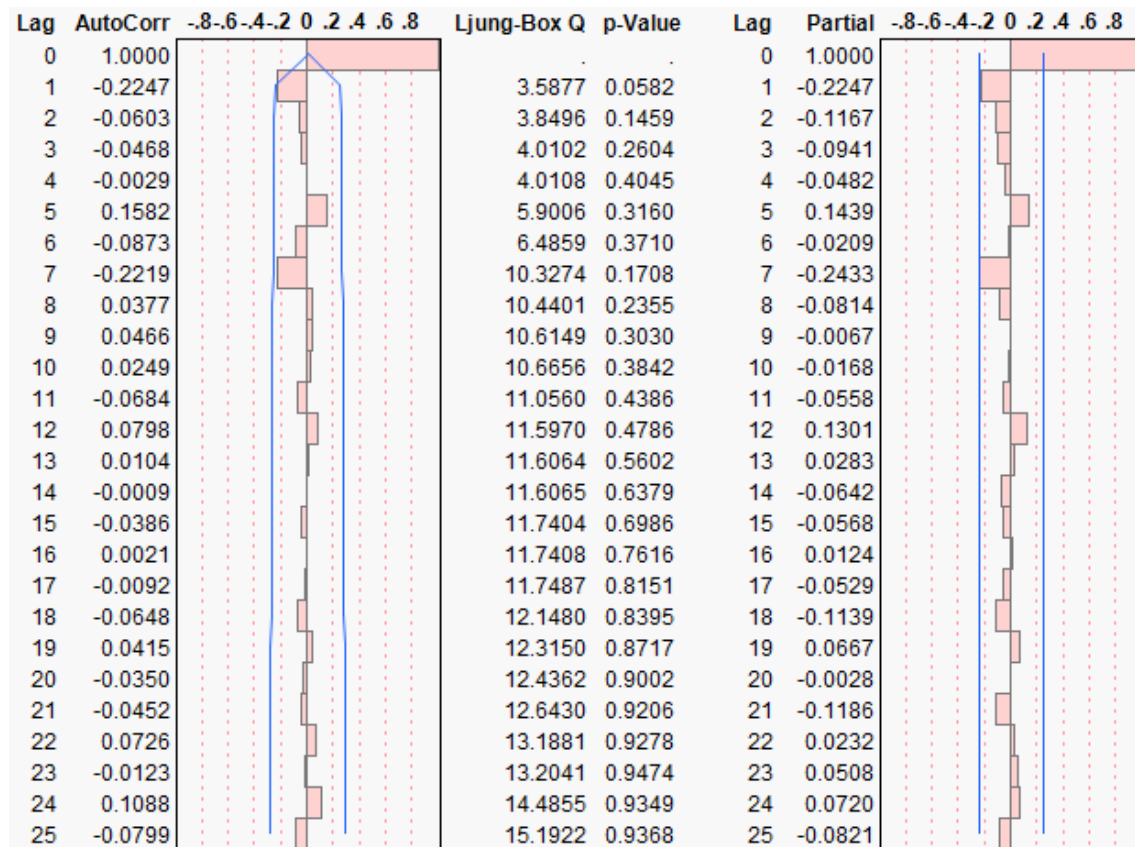


Figure 4 JMP Output of the ACF and PACF for the Cargo Demand

The ACF/PACF analysis above describes the following ARIMA forecasting model

$ARIMA(1,1,1)$. There is one AR term, one differencing transformation, and one MA term.

There is also no seasonality. Figure 5 shows the data transformation completed by subtracting

the past term from the current term to create a new working series. Figure 6 shows the

theoretical form of the $ARIMA(1,1,1)$ model. The estimated series (Figure 7) is the fully

constructed model with the actual estimated parameters.

Y_T = Actual Values
 \hat{Y}_T = Forecasted Values
 Z_T = Transformed Values
 T = Time/Period
 δ = Constant derived from Mean
 ϕ = Autoregressive Coefficient
 θ = Moving Average Coefficient
 a_T = Random Shock
 B = Backshift Operator

Table 1 Definition of ARIMA Parameters

Working Series

$$Z_T = (1 - B)Y_T = Y_T - Y_{T-1}$$

Figure 5 First Difference Transformation

$$Z_T = \delta + \phi Z_{T-1} + a_T - \theta_1 a_{T-1}$$

$$Y_T = \delta + \phi(Y_{T-1} - Y_{T-2}) + a_T - \theta_1(Y_{T-1} - \hat{Y}_{T-1}) + Y_{T-1}$$

Figure 6 Theoretical ARIMA (1,1,1) Model

$$Y_T = 23.87 + (0.47)(Y_{T-1} - Y_{T-2}) + a_T + (0.76)(Y_{T-1} - \hat{Y}_{T-1}) + Y_{T-1}$$

Figure 7 Estimated ARIMA(1,1,1) Model for Cargo (tons)

When estimating a model, diagnostic procedures are followed to ensure that the model is adequate. This is done through residual analysis. If the appropriate AR and MA orders have been identified, the residuals of the observations are transformed to white-noise processes. The residual ACF and PACF are reviewed to determine if there is any significant structure left in the data that was not identified. If there is no significant difference between the lags, the residuals indicate the current form of the model is good. The Ljung-Box statistics for each lag determines whether or not there is a relationship between the residuals, if there is not, then the value is small indicating that the model is adequate. We see below in Figure 7 that there are no significant lags as well as no significant Ljung-Box values and the associated p-values are also large indicating

the same. Additionally, there are near significant terms at the 7th lag on both charts. It would be worth experimenting with a seasonal model to reduce the autocorrelation further.

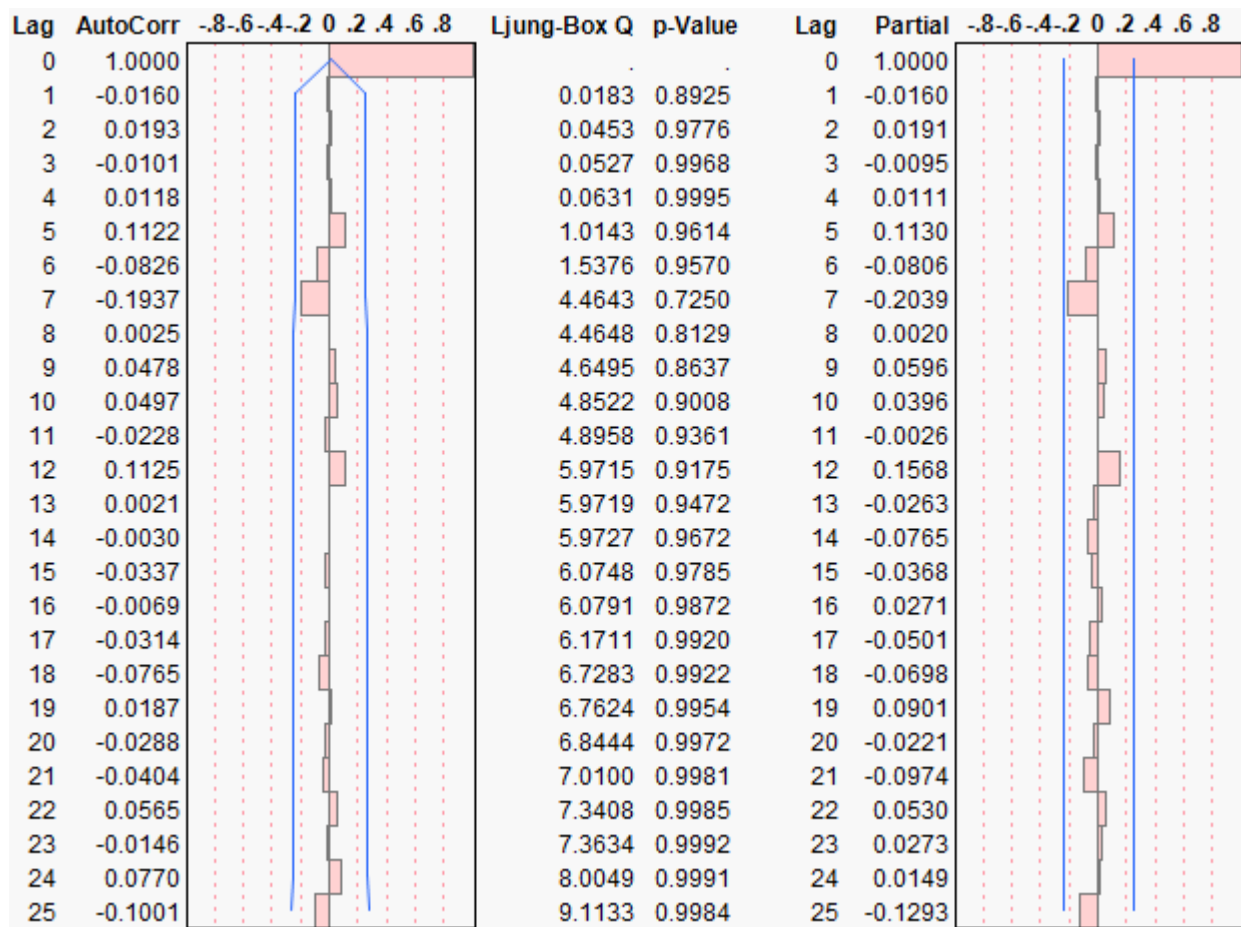


Figure 8 RACF and RPACF for ARIMA(1,1,1) Cargo Model

Once the model is developed and determined to be adequate, the model development process is complete. The next step is to determine whether or not that model in particular is the best one for the data set at hand. A variety of goodness of fit checks can be used for the model selection and comparison. A brief description accompanies the more important criteria below.

The mean squared error (MSE) measures the variability in the forecast errors with the goal of small variability in the forecast errors. The MSE is a direct measure of the variability of a one-step ahead forecast error (Montgomery, Jennings, & Kulahci, 2008).

$$MSE = \frac{1}{n} \sum_{t=1}^n [e_t(1)]^2 \quad (1)$$

A maximally valued R^2 statistic is equivalent to minimizing the sum of the squared residuals (Montgomery, Jennings, & Kulahci, 2008). Large values of the statistic represent a good fit of the predicted values to the historical data. One has to be careful in using this value as it can be easily inflated by adding insignificant parameters to the model. Having a parsimonious model is usually preferred when dealing with regression models or time series models.

$$R^2 = 1 - \frac{\sum_{t=1}^T e_t^2}{\sum_{t=1}^T (y_t - \bar{y})^2} \quad (2)$$

The Akaike Information Criteria (AIC) and the Schwarz Information Criteria (SIC) are both similar criteria that penalize the sum of squared residuals for including insignificant parameters in the model (Montgomery, Jennings, & Kulahci, 2008). For both criteria, a smaller value is desired. As you can see below, the penalty for the AIC is smaller than that of the SIC. When these criteria are implemented in statistical programs, slight variations in the calculation may exist. For example, the equations below are traditional textbook equations and the program JMP (JMP 10, 2012) implements a slightly different variation of both criteria where the penalties are slightly different.

$$AIC = \ln \left(\frac{\sum_{t=1}^T e_t^2}{T} \right) + \frac{2p}{T} \quad (3)$$

$$SIC = \ln \left(\frac{\sum_{t=1}^T e_t^2}{T} \right) + \frac{p \ln(T)}{T} \quad (4)$$

The Mean Absolute Percentage Error (MAPE) and the Mean Absolute Error (MAE, also known as Mean Absolute Deviation or MAD) are shown below. The MAPE is meaningful in

that it represents a scaled size of the forecast error in the model by being displayed as a percentage. The MAE is useful depending on the unit of measurement of the dataset (Montgomery, Jennings, & Kulahci, 2008). In this case, knowing the relative size of the cargo and using the same data with different models allows us to use both criteria for model selection.

$$MAPE = \frac{1}{n} \sum_{t=1}^n |re_t(1)| \quad (5)$$

$$MAE = \frac{1}{n} \sum_{t=1}^n |e_t(1)| \quad (6)$$

An important aspect of model evaluation is to remember that none of these criteria should be used individually to select a best model. Certain criteria, the MSE, R^2 , and the AIC, do not penalize the criterion value enough for including extraneous parameters, making them inconsistent. The SIC, includes a “heavier” penalty for this, allowing for consistency and parsimonious models.

The estimated coefficients, as seen in the Figure 10, are all determined to be significant.

The goodness of fit criteria are displayed in Figure 9 below.

DF	65	Stable	Yes
Sum of Squared Errors	20774857.4	Invertible	Yes
Variance Estimate	319613.19		
Standard Deviation	565.343427		
Akaike's 'A' Information Criterion	1058.03122		
Schwarz's Bayesian Criterion	1064.68974		
RSquare	0.81897104		
RSquare Adj	0.81340091		
MAPE	23.8172955		
MAE	391.039499		
-2LogLikelihood	1052.03122		

Figure 9 ARIMA(1,1,1) Model Summary

Term	Lag	Estimate	Std Error	t Ratio	Prob> t	Constant Estimate
AR1	1	0.474403	0.27242	1.74	0.0863	23.8693125
MA1	1	0.764807	0.20308	3.77	0.0004*	
Intercept	0	45.413685	31.26421	1.45	0.1512	

Figure 10 ARIMA(1,1,1) Parameter Estimates

Developing a transfer function-noise model is a more complex process with additional steps to determine the model parameters. It may be necessary to make stationary both the input data and the output data in different manners. The next step is to prewhiten the data.

Prewhitening involves first finding an adequate ARIMA model that describes the input series (Bowerman, O'Connell, & Koehler, 2005). The next step is somewhat more complicated. Most statistical programs, in this case JMP, have the ability to prewhiten data. It uses the parameter estimates from the estimated ARIMA model on the input series and solves for prewhitened output values. The goal of which is to obtain a sample cross-correlation function (SCC) with a filtered input and a filtered output that can be used to identify the parameters of the transfer function model. The SCC is a measure of the linear relationship between the prewhitened input and output values.

The s operator measures the number of past transformed input values influence on the transformed output values. The r operator measures the number of its own past values that the output is related to. These operators are observed at both the nonseasonal and the seasonal level just like in standard ARIMA model development. These appropriate operators can now be input into the general transfer function model to determine if all of the parameters are in fact significant to the model or not. At this point, none of the parameters for the output series have yet been estimated. The residual ACF and PACF charts must be analyzed once a parsimonious input model has been found. The residual ACF and PACF charts identify an appropriate ARIMA model to describe the error terms, or the residual cargo data unaccounted for by the input model. The final transfer function model is thereby obtained by the error term ARIMA model and the transfer function inputs. The same model adequacy process must be continued at this point to determine if all parameters are in fact significant, if the residuals are not significant, and to determine if enough correlation is accounted for by the model. Continuing this process resulted in two significant transfer function models to compare with the other models presented above.

Forecasting Demand

For many years now, forecasting has been taken into consideration for operational planning in the civilian world. Manufacturers (ex. car companies), airline companies, city planners, hospitals, and many other areas, businesses, or institutions incorporate mathematical or statistical methods in their strategic planning for future operations. Managers or executives have long been asked to make a decision about the future and can potentially benefit by applying the general principles of forecasting. One of the first decisions to make is what type of forecasting is necessary for the problem at hand. There are two types to consider, qualitative or quantitative, and the selection depends on the context of the forecast, availability of data, the accuracy needed, the period to forecast, and the cost/benefit of the forecast (Chamber, Mullick, & Smith, 1971). By weighing these factors, a decision maker can choose an appropriate method or technique for the problem at hand.

Qualitative forecasting is used when data are not available; therefore, logical judgment is used to estimate factors. Quantitative forecasting incorporates both time series methods and causal models. Time series techniques are beneficial when several years of data are available and helps identify and explain seasonality, cyclical patterns, trends, or growth rates of the trends within the data. Casual modeling is the most mathematically complex form of forecasting and analysis. Mathematics expresses relationships within the data or between different variables and can account for cause and effect relationships from events as well. (Chamber, Mullick, & Smith, 1971) For the issue at hand, complexity is necessary in order to increase the accuracy of the forecast and to ensure that the historical data could produce beneficial results.

Although the current problem is directly related to airlifting cargo, there are many other examples of forecasted demand using the same techniques. Studies have been conducted using

demand forecasting for semiconductor companies to determine investment and manufacturing strategies for capacity planning. Semiconductors have no relation to cargo, but as shown, time series methods have been applied in many companies that are increasingly dependent on future demands. The semiconductor research proposed using a multi-generation diffusion model that involving multiple input factors that changed across technological generations (Chien, Chen, & Peng, 2008). The complexity and broadness of this type of model is not necessary for this problem, but presents a very interesting approach that provides good fitting models and precise forecasts.

Forecasting cargo demand is quite common. Companies such as Federal Express use forecasting models to forecast their cargo growth into the future to plan for acquisitions and site expansions (Datamonitor, 2011). Many states provide basic forecasts of cargo shipments into their state as a measure of potential profitability. California and Florida specifically have done extensive studies about the future of air cargo tonnage in their states and the impact it presents on their current airport capabilities (TranSystems, 2010; Air Cargo Tonnage Forecast and Capacity Analysis, 2005). However, these analyses only look at past trends and uses naïve forecasts based on numbers from the shipping companies.

More advanced air-cargo demand forecasting has been approached in recent years as well, as it is one of the key issues of airline revenue management. A new technique called support vector machine (SVM) model was applied to cargo-volume data from Beijing and then compared Brown's Cubic exponential smoothing model (Heng, Zheng, & Li, 2009). The accuracy of the SVM forecasting model is more accurate than Brown's model; however, more research needs to be conducted in the application of structure based learning models to determine if SVM is generally better at time series prediction. Although this technique may be useful in the

future, a black or grey box approach is not as valuable to the user at this time due to a more difficult implementation.

More traditional time series forecasting approaches as mentioned in the previous section are easily implemented and automated. As we show in the next section, these types of models are also quite precise as well. The research did not provide a direct application of exponential smoothing methods or ARIMA methods used on airlift or cargo demand, but still produced other forecasting demand applications that are just as beneficial. Time-series forecasting using ARIMA and SARIMA methods to estimate future primary energy demand of Turkey from 2005 to 2020 have been shown to be reliable methods (Ediger & Akar, 2007). Energy forecasting dates back to the 1960s and recent studies have applied regression, auto regression, genetic algorithms, ARIMA, SARIMA, and neural network methods to historical data. Research has shown that the parameters used in these various methodologies usually deviate from the actual values, making the forecasts unreliable. By using ARIMA or SARIMA, the additional parameters can be eliminated and the energy demand can be estimated by its own time series. The final results showed that the ARIMA and the SARIMA models were both efficient and reliable for forecasting of energy demand based on the type of energy.

Further research provides an excellent comparison of SARIMA and artificial neural networks (ANN) to forecast cement demand (Liu, Chen, Yang, Hung, & Tsai, 2008). The study compares the forecast accuracy of the two methods. ANN is a complex modeling approach that most mathematical or statistical packages now implement. The black box work of an ANN involves continuously adjusting weighted values applied to the inputs until the network output reaches a target value. The conclusion was that the ANN can provide a more accurate demand forecast without the addition of functions to account for outside influences. The SARIMA

performed well, but needs possible modification to an intervention model to account for holidays, weather, and economic cycles.

Summary

There is no single best forecasting method. The selection of the appropriate model has many determining criteria and is subjective to the output, the available information, and the user. The literature has expressed that forecasting is both an art and a science and the development of the model depends on both the analytical steps developed and what constitutes a pattern or a significant feature. This study compares forecasting techniques through application and provides analysis as to which method is preferred for the problem of predicting cargo demand.

III. Methodology

This section discusses the development of the forecasting models and the cargo scheduling heuristic constructed to simulate Dover AFB aerial port airlift to Afghanistan.

Scope and Data Description

The TACC Strategic Airlift Simulation (TACCSAS) is constructed as a tool to test the usefulness of previously constructed airlift schedules and to forecast future demand and evaluate potential airlift schedules. TACCSAS allows the user to simulate scheduling cargo pallets and airlift for a specific month based on previously constructed schedules, or to forecast a full year, one quarter, or a single month ahead. All pallets travel from Dover AFB using CRAF aircraft and Organic military aircraft previously purchased or scheduled for that month. The user selects the period that they would like to simulate and then selects the simulation parameters to include number of runs and cargo pallet weight distribution parameters. The user determines available numbers of aircraft types, can add and delete aircraft available for transport, change aircraft capability parameters, and add or delete scheduled aircraft departures. Once the simulation has run, the user can view and compare the collected statistics. TACCSAS was constructed entirely using Microsoft Excel Visual Basic for Applications (VBA) (Microsoft, 2007). Examples of TACCSAS operations and further description are provided in Appendix E.

The data used for forecasting is provided by GATES. GATES is an automated aerial port processing system that aids in scheduling of unit and cargo movement and shipment forecasting. (Westcott, 2006) The GATES data sets are generated by fiscal year (FY) and include 31 categories by which to sort the data. These categories include pallet ID number, date of pallet arrival, gross pallet weight, mission ID numbers, aerial port of departure (APOD), aerial port of embarkation (APOE), and departure date among many others. To ensure adequate models could

be developed, GATES reports for FY2005 through FY2010 are split into monthly cargo totals shipped into Afghanistan. Pallet data from FY2011 is separated and used validation. The issue with the GATES data outputs is that the cargo report generated includes all cargo entries from all APOEs to all APODs for every mission type. This allows for FY report to include anywhere from 275,000 to 325,000 individual entries. Figure 11 shows the mission character codes observed and filtered to simplify the data set. Under Second Character, only channel cargo is observed, so all mission IDs including the character “B” are retained. Under Third Character, all missions are retained except those IDs that include “C” or “P.”

Second Character		Third Character	
B	Channel Cargo	A	Not Assigned*
J	Positioning to first onload	B	Distribution Channel, Atlantic Region*
K	Channel PAX	C	Distribution Channel, Pacific Region*
L	Aeromedical Evacuation (AE)	P	Not Assigned*
Q	Channel Mixed (PAX and cargo)	E/Q	CPX Channel missions as assigned by 18 AF/A3Y
V	Depositioning from offload to new mission or home station	J/R/U W/Y/Z AOC/XOP	Channel missions supporting Contingency Operations. Coordinate ID with 618

Figure 11 AMC Mission Character Codes (AMC/A3CF, 2012)

The research focuses on cargo channel missions directed to Afghanistan. To reduce the data set even further, only entries that departed from Dover AFB and arrived in Afghanistan are considered. The data set includes repeat pallet entries, which occurred whenever an individual pallet was transferred to a different aircraft. Only considering the pallets that entered into Afghanistan filtered out the repeated pallet entries. The data were then sorted by month and summed into a single tonnage scheduled for that month. The monthly totals are used to generate the forecasting models. Monthly totals are used to accommodate the monthly BOG input. Weekly BOG values were unattainable.

Model Selection

All of the approaches described in Chapter 2 are applied to the problem. The result is a detailed comparison of 11 different models.

Chapter 2 presented a number of different criteria to evaluate the goodness of fit of the models that are developed. Below is a detailed chart of 9 of the 11 models that are developed as are summarized by JMP. The two regression models are not included in the chart due to the limitations of the JMP program. All of the models are good models according to the criteria presented. The smoothing methods provided the best results and the next best are the transfer functions. The standard ARIMA models had too much variance between the predicted and the actual values.

If it were only a matter of choosing the best, one would easily choose Transfer Function Model (1) as its criteria are better in most aspects. However, the best way to evaluate a model is validation via data splitting. Data splitting divides the data into two segments, one to fit the model and one to evaluate the model (Montgomery, Jennings, & Kulahci, 2008). The benefit of this technique is the knowledge of how the model will perform on new data and to compare competing models. Data splitting is performed on the 12 cargo values for FY11. All 11 models provided 12 month forecasts.

Model	DF	Variance	AIC	SBC	RSquare	-2LogLH	MAPE	MAE
Seasonal Exponential Smoothing(12, Zero to One)	54	285043.11	885.17672	889.22743	0.800	881.17672	25.763687	460.09723
Winters Method (Additive)	53	290421.28	887.17672	893.25278	0.800	881.17672	25.763687	460.09723
Transfer Function Model (1)	63	271794.88	1032.7003	1041.5191	0.851	1024.7003	21.399069	344.39029
Transfer Function Model (2)	63	278510.57	1034.3099	1043.1287	0.847	1026.3099	22.926044	363.81241
Double (Brown) Exponential Smoothing	66	363739.08	1051.0052	1053.2099	0.780	1049.0052	23.919009	428.18849
Simple Exponential Smoothing(Zero to One)	67	320377.63	1056.1085	1058.3280	0.813	1054.1085	22.196737	392.09033
IMA(1, 1)	66	321788.61	1057.4012	1061.8402	0.815	1053.4012	23.179941	394.41567
ARIMA(1, 1, 1)	65	319613.19	1058.0312	1064.6897	0.819	1052.0312	23.817296	391.03950
ARI(1, 1)	66	327632.66	1058.5760	1063.0150	0.812	1054.576	23.031031	397.05670
Seasonal ARIMA(0, 1, 1)(1, 0, 1)12	64	290546.15	1059.3699	1068.2479	0.822	1051.3699	23.096380	389.21300

Figure 12 JMP Output - Model Selection Criteria

Data splitting may not always be an option. The purpose of forecasting is to provide a prediction for the future, often times eliminating the ability to validate results. For this reason, goodness-of-fit criteria provide standardized evaluation methods to determine which model best fits the data. In addition to the criteria, one must apply common sense to the evaluation. If the model maps the data set near perfectly, but provides extreme forecasts, then the criteria are not useful and neither is the model.

Table 2 indexes each model developed. Throughout the model selection process each model is referenced by its specific number.

Model 1	Linear Regression
Model 2	Intervention
Model 3	Simple Exponential Smoothing
Model 4	Double Exponential Smoothing
Model 5	Seasonal Exponential Smoothing
Model 6	ARIMA(1,1,1)
Model 7	ARI(1,1)
Model 8	IMA(1,1)
Model 9	Seasonal ARIMA (0,1,1)(1,0,1) ₁₂
Model 10	ARIMA(1,0,0) / ARIMA(0,1,1)
Model 11	ARIMA(0,0,1) / ARIMA(0,1,1)

Table 2 Model Number Designators

To select the best fitting model among such similarly valued selection criteria, data splitting is employed by holding out FY2011 cargo demand data from the forecast. A 12-month forecast is conducted for each model and then compared with the actual FY2011 results shown in Table 2. The residuals are then used to compute the percentage deviation from the actual results shown in Table 3. The research shows that some of the models only predict the first month and use that value for all of the following forecasts. Other models have adjusted values for each month. Some of these models incorporate some degree of seasonality in the data, whether from

the Tons of Cargo or from the BOG input. There is no expectation that the model can accurately predict a full years worth of cargo demand, but a fair estimate is necessary. The critical forecasts are the ability to predict a quarterly buy (3 month forecast) or a monthly buy (1 month forecast).

Date	Tons of Cargo	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Oct-10	3,300.60	4,922.26	4,074.61	3,306.13	3,187.91	3,635.69	3,512.38	3,235.07	3,399.52	3,503.98	3,510.47	3,635.99
Nov-10	4,149.92	4,922.26	4,540.01	3,306.13	2,924.94	3,520.29	3,779.81	3,227.67	3,439.99	3,481.50	3,725.43	4,090.68
Dec-10	4,536.60	4,922.26	4,862.79	3,306.13	2,661.98	3,619.96	3,930.55	3,276.24	3,480.45	3,547.50	3,785.59	3,940.11
Jan-11	5,069.22	4,922.26	5,082.43	3,306.13	2,399.01	3,752.85	4,025.93	3,311.95	3,520.92	3,624.14	3,765.92	3,797.04
Feb-11	4,852.68	4,922.26	4,929.59	3,306.13	2,136.05	3,783.84	4,095.04	3,350.61	3,561.38	3,661.37	3,706.01	3,661.09
Mar-11	4,529.13	4,922.26	5,040.70	3,306.13	1,873.08	4,480.50	4,151.70	3,388.59	3,601.85	4,002.25	3,626.78	3,531.91
Apr-11	4,037.11	4,922.26	5,232.21	3,306.13	1,610.12	4,461.58	4,202.45	3,426.73	3,642.31	4,016.71	3,539.20	3,409.17
May-11	4,370.84	4,922.26	5,042.36	3,306.13	1,347.15	4,284.65	4,250.39	3,464.84	3,682.78	3,959.10	3,449.01	3,292.55
Jun-11	5,318.32	4,922.26	4,982.95	3,306.13	1,084.19	4,401.08	4,297.01	3,502.95	3,723.24	4,035.31	3,359.19	3,181.73
Jul-11	3,691.94	4,922.26	4,863.00	3,306.13	821.22	4,349.26	4,342.99	3,541.06	3,763.71	4,034.77	3,271.24	3,076.43
Aug-11	4,014.77	4,922.26	4,734.02	3,306.13	558.26	4,295.82	4,388.68	3,579.17	3,804.17	4,033.49	3,185.88	2,976.38
Sep-11	4,941.08	4,922.26	4,423.57	3,306.13	295.29	3,732.69	4,434.22	3,617.28	3,844.64	3,799.72	3,103.44	2,881.31

Table 3 Actual Tons of Cargo vs. Predicted Tons of Cargo

Date	Tons of Cargo	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Oct-10	3,300.60	49.13%	23.45%	0.17%	3.41%	10.15%	6.42%	1.99%	3.00%	6.16%	6.36%	10.16%
Nov-10	4,149.92	18.61%	9.40%	20.33%	29.52%	15.17%	8.92%	22.22%	17.11%	16.11%	10.23%	1.43%
Dec-10	4,536.60	8.50%	7.19%	27.12%	41.32%	20.21%	13.36%	27.78%	23.28%	21.80%	16.55%	13.15%
Jan-11	5,069.22	2.90%	0.26%	34.78%	52.67%	25.97%	20.58%	34.67%	30.54%	28.51%	25.71%	25.10%
Feb-11	4,852.68	1.43%	1.58%	31.87%	55.98%	22.03%	15.61%	30.95%	26.61%	24.55%	23.63%	24.56%
Mar-11	4,529.13	8.68%	11.30%	27.00%	58.64%	1.07%	8.33%	25.18%	20.47%	11.63%	19.92%	22.02%
Apr-11	4,037.11	21.93%	29.60%	18.11%	60.12%	10.51%	4.10%	15.12%	9.78%	0.51%	12.33%	15.55%
May-11	4,370.84	12.62%	15.36%	24.36%	69.18%	1.97%	2.76%	20.73%	15.74%	9.42%	21.09%	24.67%
Jun-11	5,318.32	7.45%	6.31%	37.84%	79.61%	17.25%	19.20%	34.13%	29.99%	24.12%	36.84%	40.17%
Jul-11	3,691.94	33.32%	31.72%	10.45%	77.76%	17.80%	17.63%	4.09%	1.94%	9.29%	11.40%	16.67%
Aug-11	4,014.77	22.60%	17.91%	17.65%	86.09%	7.00%	9.31%	10.85%	5.25%	0.47%	20.65%	25.86%
Sep-11	4,941.08	0.38%	10.47%	33.09%	94.02%	24.46%	10.26%	26.79%	22.19%	23.10%	37.19%	41.69%

Table 4 Percentage Deviation from Actual Tons of Cargo

It can be difficult to visualize the differences between the models when looking at a chart of numerical values or percentages. The figures below provide a visual representation of all of the models predicted values compared to the actual tons of cargo. The benefit of the charts is that one can see how closely the models follow the entire five year sequence of actual values as well as the disadvantages of the forecasted values. It is quite apparent which models attempt to forecast with any degree of accuracy and which models are only capable of providing a one-step ahead forecast. Seasonality can be important in forecasting as it allows for increases and decreases correlated with certain seasonal trends. Unfortunately, in some models the seasonality can sway the predictions in the wrong direction based on prior trends. Judging by appearance, there appears to be one stronger model or better estimating model that stands out in each chart in Figure 13, Figure 14, and Figure 15. The transfer function models have the worst predictive capability in this case (Figure 16).

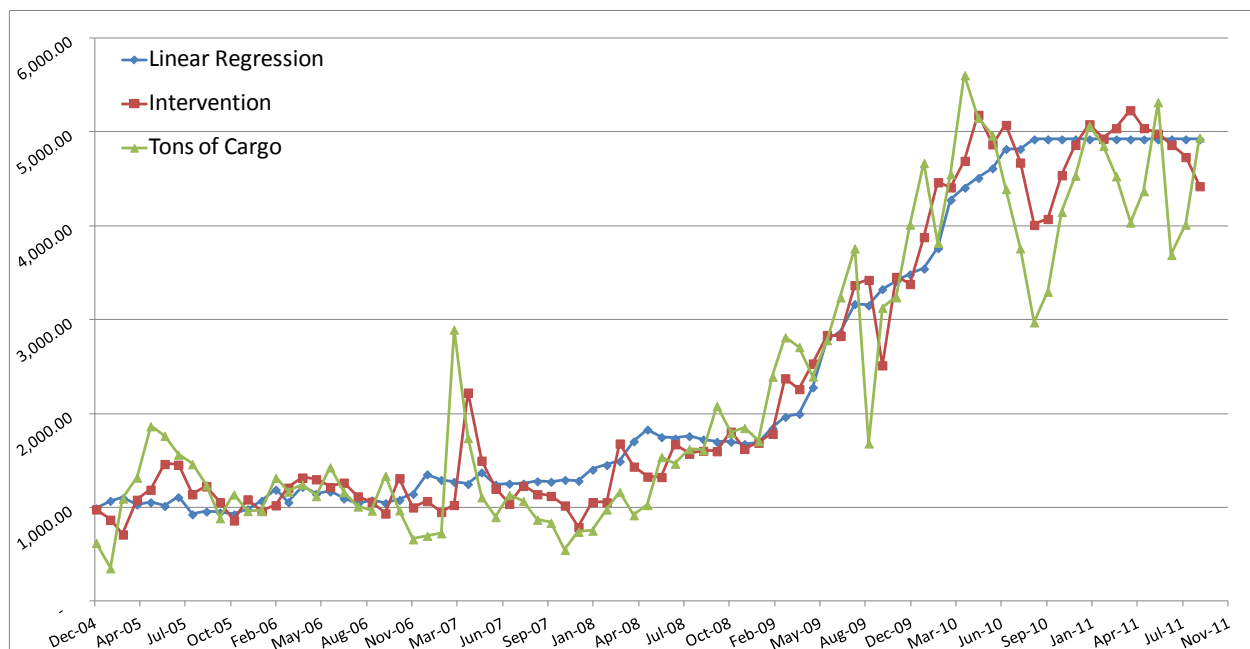


Figure 13 Tons of Cargo vs. Regression Models

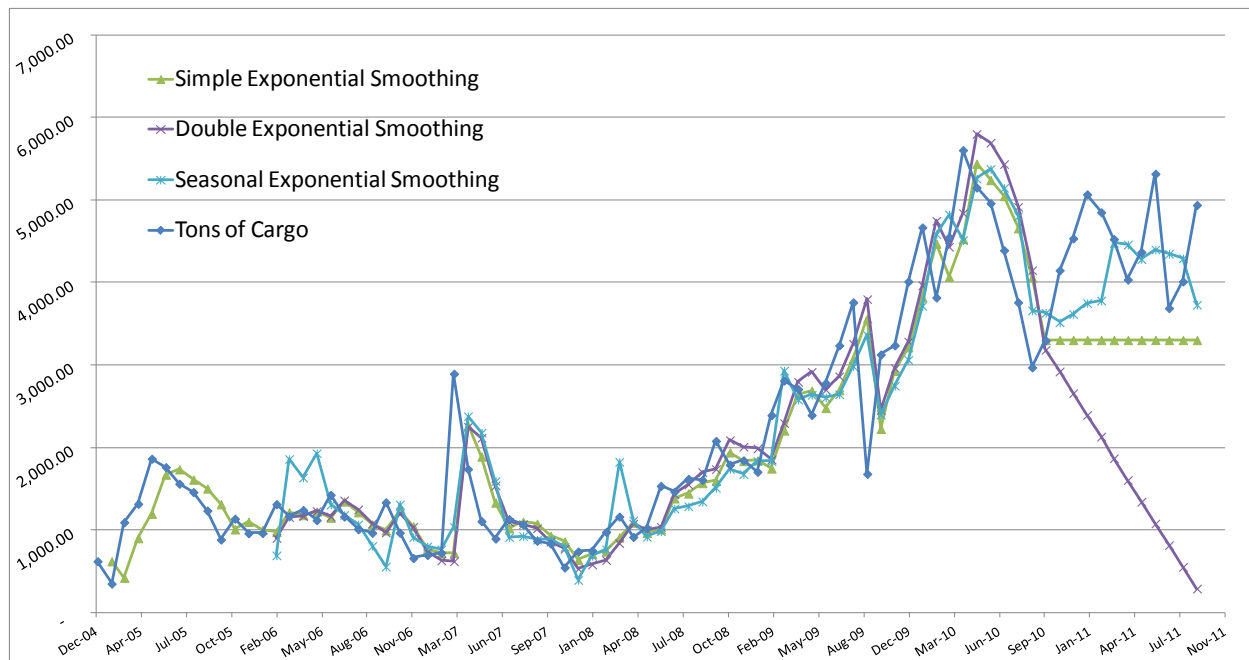


Figure 14 Tons of Cargo vs. Exponential Smoothing Models

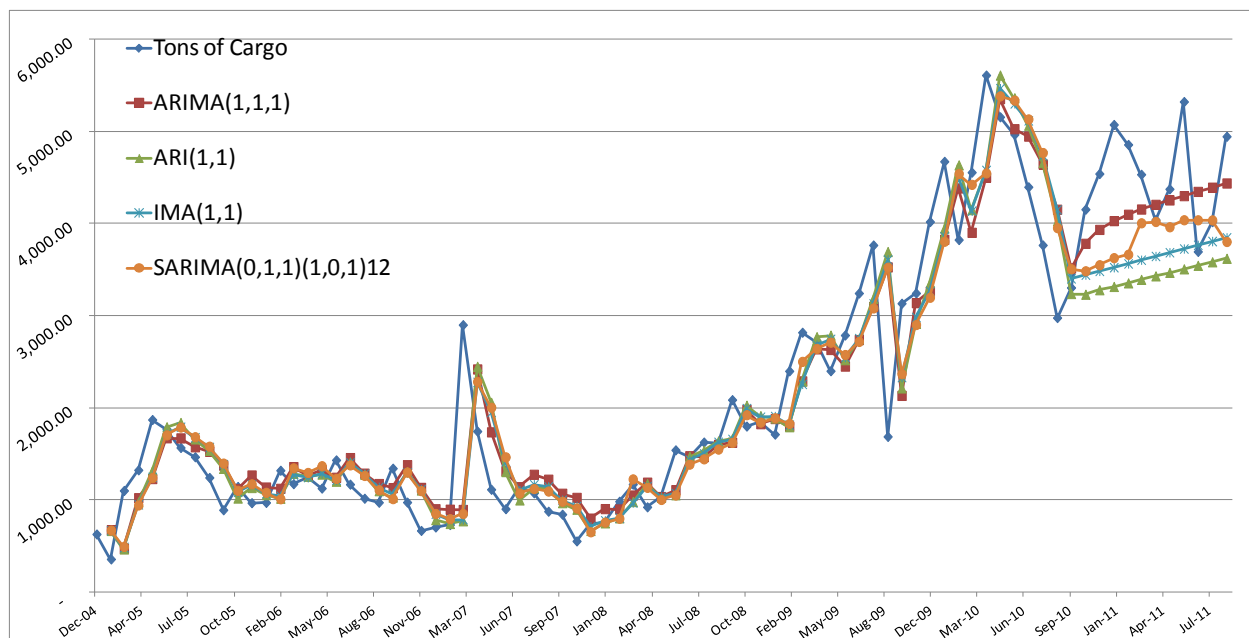


Figure 15 Tons of Cargo vs. ARIMA Models

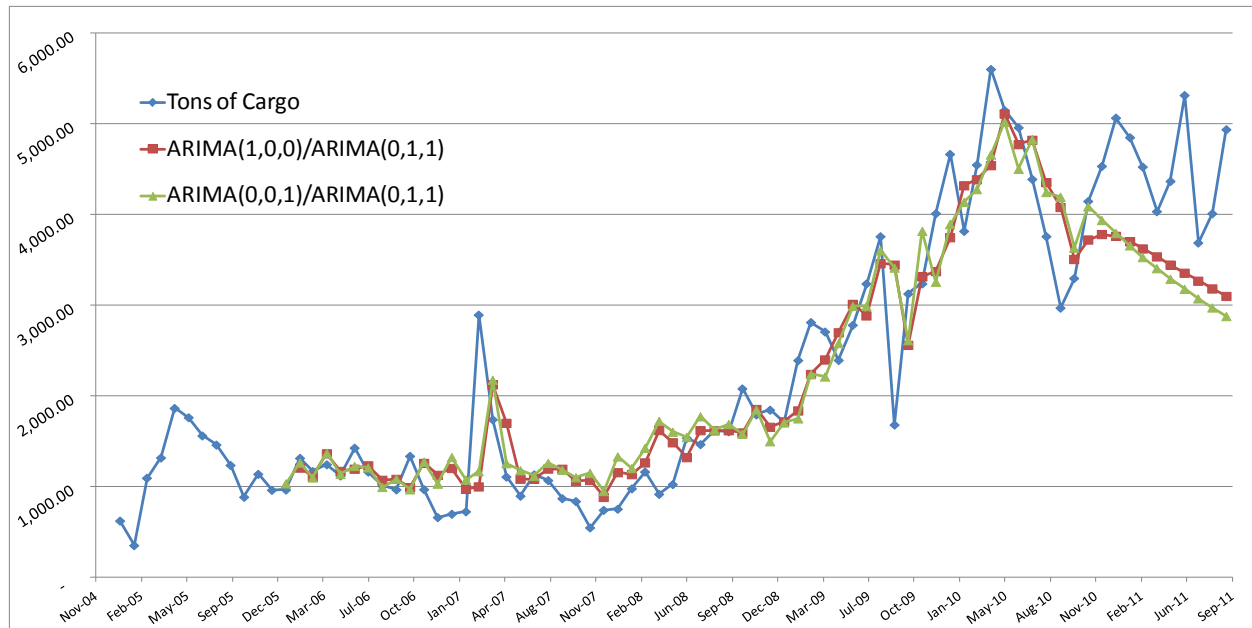


Figure 16 Tons of Cargo vs. Transfer Function Models

The three month forecast is represented below in Table 5. The field of models is narrowed down by observing the percentage deviation on a three month forecast. The absolute deviation measures the accuracy of the prediction. Percent deviation is equal to $|\text{Actual} - \text{Forecast}| / \text{Actual}$. For this forecasting application, it is not as important to measure the increase or decrease of the forecast from the actual value. If the forecast is too high, too many aircraft are reserved and cancellations will occur, and the cost to schedule will be incurred. If the forecast is too low, then “expansion buys” will have to be completed and additional money will be spent. The deviations in the forecasts in Table 5 appear to steadily increase due to larger increases from October 2010 to December 2010 in the data set. In this situation, planning would remain slightly ad hoc, but a foundation of scheduled aircraft can still be established from the forecast. Once the next data point is included into the data set, all models need to be rerun and a new best fitting model selected. Rerunning the models with all available data includes the most recent changes and the better models will begin to react appropriately. The downfall to the simulation is if the

forecasts happen to be low for the upcoming months, then the planners make more purchases for the monthly buy.

Actual vs Predicted							
Date	Tons of Cargo	Model 1	Model 2	Model 5	Model 6	Model 8	Model 9
Oct-10	3,300.60	4,922.26	4,074.61	3,635.69	3,512.38	3,399.52	3,503.98
Nov-10	4,149.92	4,922.26	4,540.01	3,520.29	3,779.81	3,439.99	3,481.50
Dec-10	4,536.60	4,922.26	4,862.79	3,619.96	3,930.55	3,480.45	3,547.50

Residuals							
Date	Tons of Cargo	Model 1	Model 2	Model 5	Model 6	Model 8	Model 9
Oct-10	3,300.60	(1,621.66)	(774.01)	(335.09)	(211.79)	(98.92)	(203.38)
Nov-10	4,149.92	(772.34)	(390.09)	629.62	370.11	709.93	668.42
Dec-10	4,536.60	(385.65)	(326.19)	916.64	606.06	1,056.15	989.10

Percentage Deviation							
Date	Tons of Cargo	Model 1	Model 2	Model 5	Model 6	Model 8	Model 9
Oct-10	3,300.60	49.13%	23.45%	10.15%	6.42%	3.00%	6.16%
Nov-10	4,149.92	18.61%	9.40%	15.17%	8.92%	17.11%	16.11%
Dec-10	4,536.60	8.50%	7.19%	20.21%	13.36%	23.28%	21.80%
Average % Deviation		25.41%	13.35%	15.18%	9.56%	14.46%	14.69%

Table 5 Quarterly Buy Forecast Comparison

The one month forecast is represented in Table 6. Since all of the models are similar in their predictive ability, with the exception of Model 1, the same set of five models are compared for the one month forecast. All of the models are very close when it comes to one month forecasting, however, the Model 8 stands out above the rest. Further data splitting analysis is conducted on the five remaining models in Chapter 4.

Actual vs Predicted

Date	Tons of Cargo	Model 2	Model 5	Model 6	Model 8	Model 9
Oct-10	3,300.60	4,922.26	3,635.69	3,512.38	3,399.52	3,635.99

Residuals

Date	Tons of Cargo	Model 2	Model 5	Model 6	Model 8	Model 9
Oct-10	3,300.60	(774.01)	(335.09)	(211.79)	(98.92)	(203.38)

Percentage Deviation

Date	Tons of Cargo	Model 2	Model 5	Model 6	Model 8	Model 9
Oct-10	3,300.60	23.45%	10.15%	6.42%	3.00%	6.16%

Table 6 Monthly Buy Forecast Comparison

Modeling Approach

The modeling approach was initially a reverse concept to determine whether or not optimization of CRAF on a monthly basis was necessary and to determine what the cost savings are. In this case, cost savings are determined by the number of cancellations generated on a monthly basis. As described in Chapter 1, it may seem counterintuitive that savings involve paying to cancel a plane; however, the cancellation cost is only ~20% of the flight cost. If cargo loading is optimized on specific types of CRAF airframes, then it is easy to calculate the approximate number of aircraft necessary to move a certain number of cargo pallets or cargo tons. The simulated number of aircraft used to airlift the cargo pallets is then compared to the actual number of aircraft used, with the difference in numbers turning into immediate savings.

This report previously mentions the use of simulation for operational planning, specifically Monte Carlo simulation. Monte Carlo simulation is a method of analysis (usually using a computer) to recreate a random process many times in a model of a real system to study and understand the system (Barreto & Howland, 2006).

Fortunately, an initial framework of the Monte Carlo simulation was constructed by Lindstrom in his Graduate Research Project (GRP) (Lindstrom, 2012). The previous solution

was reworked into TACCSAS to provide quick answers by selecting a few options. By reworking the problem from the beginning, the new system is now more robust and flexible to meet the needs of TACC.

To simulate the actual process, Monte Carlo simulations of a selected month are run using randomized parameters calculated based on distributions modeling the actual pallet data. The real time data required to perform the operational planning aspect is the pallet data. The weight of the pallet, the destination of the pallet and the arrival date of the pallet to the base are the three important components. These three parameters are randomly produced with each run to fill a realistic schedule. The randomized weights of the pallets are provided by selecting one of the following distributions: Exponential, Lognormal, Normal, Weibull, or Triangular. Once a distribution is selected, the distribution parameters from the past pallet data from the selected month are calculated and used as the basis for the random weight distribution. For example, if the normal distribution is selected to simulate the pallet weight from October, then the mean and the standard deviation from the past October's pallet data is calculated and used to produce a predetermined number of random pallet weights. A random destination location is then assigned to each individual pallet based off of the distribution of the actual destination locations from the selected month. For example, the month of October may show that 40% of the actual scheduled pallets are destined for Kandahar, 30% to Bagram, and 30% to Bastion; the pallet locations are then randomly assigned to follow this discrete distribution. A random date is also assigned to each pallet simulated. The dates are drawn from a discrete distribution derived from the actual past month's pallet data. A sample of the actual aircraft schedule, actual pallet schedule, discrete distribution, and Monte Carlo Simulation is viewed in Appendix D. These three components

then make up a simulated full month of pallets that are sorted by date, then location, and are assigned to individual aircraft.

Sometimes in Operations Research, there are problems that require too much computational time to solve exactly or may require an approximate solution method due to the nature of the problem. In these cases, constructive methods known as heuristics are useful for finding good, yet not exact, solutions. Given more time and more fidelity in the data available, an optimal solution may have been possible for the problem, however, heuristics methods have allowed for a good feasible solution with room for sensitivity analysis. There are many benefits to heuristic methods; the biggest may be that they tend to be common-sense approaches that are tailored to the specific problem (Metaheuristics, 2005). As seen in the section Cargo Loading Algorithm, heuristic methods are often iterative algorithms where each iteration conducts a new search for a better solution.

After the heuristic, known as the cargo loading algorithm, was developed for the pallet assignment, the forecasting portion was incorporated to allow for the operational planning aspect of the problem in addition to the sensitivity analysis portion.

Model Inputs

The first input required is the cargo tonnage forecast generated from the cargo forecast models. The model requires an estimated number of pallets for a single month period. The number of pallets is derived from the weight distribution assigned to the cargo pallets. For example, if TACC will airlift 3,000 tons of cargo in January to Afghanistan, and the average pallet weighs 2 tons, then the simulation input is 1,500 pallets. The pallet weight is then normally distributed with the mean and the variance generated by the GATES data and using the minimum pallet weight as a floor for the distribution to prevent negative pallet weights. The

model then assigns the pallets to the existing CRAF airframes in the current inventory based on the route that the airframes are assigned. Once all the pallets are assigned or once all of the available aircraft are filled either with minimum number of pallets or by the minimum number of tons, the problem completes and the statistics (averaged by number of runs) are displayed.

Cargo Loading Algorithm

The main objective of the problem is to move as much cargo as possible as efficiently as possible. The ACL constraints allow for the additional objectives of minimizing the number of aircraft used and minimizing the cost of the airlift schedule achieved in the process. Due to the current operations of USTRANSCOM, the algorithm fills CRAF aircraft flying directly to an AOR location first before filling Organic aircraft going to the same location on the same day. For this research, cargo with an assigned destination is only loaded onto an aircraft with the same destination.

The algorithm is initialized after receiving three initial inputs: the weight of the individual pallets, the APOD of the pallet, and the date of departure from DOVER AFB. Once received, either through simulated data or from the actual cargo data, the first phase of the algorithm assigns pallets to available CRAF. The algorithm examines pallets in the sorted order of date available, then APOD. It then determines if any CRAF aircraft are flying on that date and going to that APOD. The pallets available for shipping on that day or that had not yet been shipped the previous days to the same location are assigned to the available aircraft. Loading pallets continues until the weight limit is met or until all of the pallets slots are filled. This process is repeated until all aircraft available for flying on that date are filled to capacity or until all of the pallets have been loaded, whichever occurs first.

If there are no CRAF aircraft available for airlift on that specific day and going to that same location, the algorithm then moves to the second phase to determine if there are any CRAF available flying to enroute locations. If there are no enroute CRAF flights available on that day, the algorithm moves to the third and final phase to determine if any organic military aircraft are available on that date and going to that APOD. The organic military aircraft are the final attempt to transport skipped pallets. If there are no more aircraft to accommodate the available pallets, then the pallets remain on site and are moved later.

The general outline of the objectives and the constraints for the process are shown below. The objectives apply to the problem as a whole, while the constraints are applied in an iterative process checks each of these constraints in the order of the subscripts.

For each $i = 1$ to Days in Month (ex. Jan = 31 days)

For each $j = 1$ to Location Number (ex. 1 = OAKN)

For each $k = 1$ to Number of Aircraft Types (ex. B747-200 is one type)

If current aircraft = "CRAF" and current aircraft flies to j and is available on i Then

While Total tons on aircraft \leq MaxTons And Total # Pallets on Aircraft \leq MaxPallets

For each pallet not yet shipped by date i going to location j

Increment Total Tons and Total # Pallet

If Total tons on aircraft $>$ MinTons Or Total # Pallets on Aircraft $>$ MinPallets Then

Then schedule loaded aircraft

If aircraft is not loaded, then cancel

Figure 17 Cargo Loading Algorithm

System Output

TACCSAS provides individual run outputs and outputs averaged across all runs of the simulation. The averaged statistics shown in Table 7 are classified by airframe and show average allocation of pallets and utilization of the airframe.

	Simulated Pallet Statistics						
	# missions	Tonnage	Tons/msn	plt offer	pallets used	% pallets utilized	Avg pallet wt
B74710	19	1248.21	65.70	798.00	192.20	24.1%	6.51
B74720	45.8	4945.86	107.99	3068.60	765.00	24.9%	6.47
B74740	7.30	884.68	121.18	540.20	130.60	24.2%	6.78
C005A	6.00	348.10	58.02	216.00	52.60	24.4%	6.66
MD011F	20.10	1638.75	81.53	703.50	255.50	36.3%	6.42
C005B	3.70	206.54	55.87	133.20	32.40	24.0%	6.60
C017A	23.3	939.20	40.32	419.40	147.50	35.2%	6.38
Total/Avg	125.2	10211.34	81.56	46.96	12.59	26.8%	6.48

Table 7 Sample Simulation Output

The statistics give necessary info into how the available aircraft can be used. Another statistic tracked is the potential total cost if all scheduled and available CRAF aircraft are utilized during the simulated month. The cost of the simulated schedule is calculated with the cost savings as the difference between the number of CRAF actually used and the number of CRAF available. The total cost includes a cancellation fee of \$100,000. For validation purposes, and to determine if the simulation is beneficial, cost savings are calculated by comparing the simulation to the actual schedule used (Table 14).

Port hold times are also calculated. Port hold time is the amount of time a pallet spends in port until it is shipped. Large port hold times represent inefficiencies in the airlift schedule possibly due to not enough aircraft traveling, or (as will be shown in Chapter 4) poor scheduling of airlift. Due to the nature of the military's business, most cargo traveling to an AOR is important in some way and military personnel cannot afford to wait long periods of time for their

shipments. Although the focus of this research is not port hold times, it is important to monitor such important factors to determine positive or negative impacts based on the changes this research suggests. The simulation calculates port hold times for each individual pallet as the difference between the date a pallet is shipped and the date of pallet arrival at the APOE.

Model Verification & Validation

The model is verified in a step-by-step fashion. The Monte Carlo simulation is verified by reviewing randomization, the distribution, and the values of the generated pallet weights, the arrival dates, and the locations. Verification also involves stepping through the cargo loading algorithm to determine accurate loop entry, day selection, location selection and available aircraft determination. If aircraft are available, it is observed if pallets proceed to be assigned to the aircraft until the minimum or maximum constraints are met. All types of aircraft must be approached for availability if pallets still remain to be delivered. Lastly, internal run statistics are reviewed to determine if the pallets are being assigned to aircraft, if all aircraft can be filled, if the aircraft constraints are met, if all pallets are shipping when possible, and that the algorithm is moving across all three phases and is properly terminating.

Validation of the simulation involved comparison to past records and data splitting. TACCSAS provides the option to run both a simulation with random pallet data and a simulation using the actual pallet data for the specified month as pulled from the GATES records. The random pallet data uses the actual pallet number and pallet weight distributions for the specified month. Both simulations use the actual airlift schedule to ensure that the necessary parameters are properly compared. This allows the user to view the simulated pallet statistics side-by-side in matching charts. This cross check validates that the model is performing as necessary and that any statistical calculations are accurate. It also allows the user to immediately determine

whether or not the actual schedule is optimal or where improvements can be made in the future by comparing the number of pallets shipped, the tons shipped, and the number of CRAF cancelled.

	Real Pallet Statistics						
	# missions	Tonnage	Tons/msn	plt offer	pallets used	% pallets utilized	Avg pallet wt
B74710	12	796.37	66.36	504.00	438.90	87.1%	1.82
B74720	33.2	3597.19	108.35	2224.40	1944.30	87.4%	1.85
B74740	6.50	785.42	120.92	481.00	400.00	83.1%	1.97
C005A	6.00	344.77	57.46	216.00	188.00	87.0%	1.83
MD011F	14.10	962.28	68.24	493.50	476.20	96.5%	2.02
C005B	1.80	95.17	52.82	64.80	56.60	87.2%	1.70
C017A	5.4	202.00	37.48	97.20	89.70	92.2%	2.26
Total/Avg	79	6783.21	85.86	51.66	45.49	88.1%	1.89

Table 8 Example of Simulation Results with Actual Pallet Data

Summary

There are three very distinct components to the problem methodology. The first portion required sorting and parsing the original GATES data set for FY 2005-2011. Excel macros are developed to perform these actions and to separate the information necessary for a month-by-month examination. The reduced data is compiled with a single monthly cargo demand time series used to develop an appropriate forecasting model. A number of suitable models are constructed that provided accurate forecast data. After observing each model in different forecasting scenarios, the set was cut down to the five best models. These models are further evaluated in Chapter 4. The final component was to develop a simulation of a monthly pallet schedule and individual pallet weights to be assigned to a predetermined aircraft schedule. The simulation includes a cargo loading algorithm that assigns available pallets to available aircraft based on day of the month and APOD.

IV. Analysis

Model Analysis

It is difficult to accurately provide long term forecasts; a simple trend may increase or decrease deviations through time. After finding the best five models, an iterative comparison determined which model could most accurately predict cargo tonnage for multiple scenarios. It is important to repeat the comparison process while adding in new data to see how the models accommodate the change and adjust their forecasts. For example, one of the models had a very low forecast initially for one month out, but after including the data that accounted for the drastic increase, the model corrected and began to forecast better. The question is if these models are only good in an instance or if forecasting (and these models specifically) can be regularly applied to cargo demand. This process proved that these models are capable of accommodating change and continually predicting cargo tonnage on a yearly, quarterly, or monthly basis.

The intervention model, seasonal exponential smoothing, ARIMA, IMA, and SARIMA models are all repeatedly updated by adding new observations to the data set. All of the predicted values are compared to the actual values and two models stood out: the intervention model and the SARIMA model. Although the intervention model seemed the best model, the lack of real BOG numbers caused the forecast to change when provided different real world values. These two models are better at making significant adjustments to rapid increases and decreases. This allows for relatively accurate predictions. Forecasting is by no means an exact science, but the ability to adjust to change is important. The seasonal exponential smoothing performed the worst, due to its inability to quickly respond to significant changes.

Table 9 provides a brief look into the final model analysis and selection. Each of the five models was rerun 12 times, each time adding in a new data point. The top row is the number of

observations that are included in the model development and the second row is the number of months forecasted. The percentage deviations indicate how well the models forecasting abilities adapt beginning with a full year forecast all the way down to forecasting the final month of the year. The “Avg” column on the far left is the average percent deviation of the forecasted values. The intervention model regularly performs better than all the other models. The ARIMA(1,1,1) and the IMA models are the next best models and display more improvement and greater accuracy than the last two models.

	69 obs	70 obs	71 obs	72 obs	73 obs	74 obs	75 obs	76 obs	77 obs	78 obs	79 obs	80 obs	
	12M	11M	10M	9M	8M	7M	6M	5M	4M	3M	2M	1M	Avg
Inter	13.71%	10.25%	10.29%	11.06%	11.98%	13.21%	13.57%	12.51%	15.17%	20.88%	6.23%	12.01%	12.57%
SES	14.47%	16.83%	14.86%	16.89%	22.22%	24.37%	16.54%	14.14%	16.64%	23.24%	15.31%	29.39%	18.74%
ARIMA	11.37%	12.94%	10.85%	10.91%	13.96%	15.05%	13.98%	12.34%	14.95%	23.70%	7.44%	14.02%	13.46%
IMA	11.37%	19.87%	12.30%	11.29%	17.73%	18.56%	14.95%	11.82%	14.42%	24.47%	9.40%	16.50%	15.22%
SARIMA	21.75%	18.04%	12.45%	13.61%	17.60%	19.59%	16.20%	12.58%	15.08%	20.80%	7.23%	13.95%	15.74%

Table 9 Percentage Deviation Iterative Model Comparison

Table 10 compares the one month ahead forecast accuracies. The most appropriate solution methodology for the problem requires not only a reasonable forecast for a full year, but accurate predictions for the upcoming month in order to finalize airlift schedules. Due to the nature of using real world data, there will always be instances where data points are drastically different from the previous points. This is the case with the cargo data since it depends on current operations in the AOR. Despite that, many of the forecasts are within 10% of the actual value and in some cases within 5% or less. Based on average month-to-month accuracy, the intervention model, ARIMA, and the IMA models are the best. The IMA model has a lower average than the SARIMA, but the SARIMA has closer minimum and maximum deviations. The SARIMA will be used in the simulation along with the intervention model and the ARIMA

model. Using the long-term forecast and the short term forecast, the ARIMA model provides better extended forecast values than simple exponential smoothing.

	Inter	SES	ARIMA	IMA	SARIMA
69 obs	23.45%	10.15%	6.42%	6.42%	10.16%
70 obs	3.86%	20.73%	12.88%	18.89%	19.66%
71 obs	1.82%	13.22%	7.56%	13.02%	13.04%
72 obs	8.77%	11.96%	11.37%	12.95%	11.57%
73 obs	1.76%	1.42%	1.46%	2.12%	0.67%
74 obs	5.37%	22.99%	6.40%	9.05%	12.84%
75 obs	13.80%	20.41%	14.31%	16.42%	20.96%
76 obs	1.63%	7.07%	2.52%	2.51%	4.20%
77 obs	14.69%	17.18%	15.71%	17.43%	17.75%
78 obs	37.97%	35.27%	40.05%	38.61%	35.18%
79 obs	1.24%	2.55%	2.00%	5.16%	0.99%
80 obs	12.01%	29.39%	14.02%	16.50%	13.95%
Avg	10.53%	16.03%	11.22%	13.26%	13.42%
Max	37.97%	35.27%	40.05%	38.61%	35.18%
Min	1.24%	1.42%	1.46%	2.12%	0.67%

Table 10 One Month Ahead Forecast Accuracy and Average

If forecasting is included in the normal planning procedures, the best scenario is to rerun all of the models each forecasting attempt and to compare the goodness of fit criteria, focusing on the MSE, and using whichever model is the most accurate. Unfortunately, the same model may not necessarily be applied each time; however, repeated analysis shows that the seasonal exponential smoothing model is consistently the top model of those examined. Given the validation, seasonal exponential smoothing was not be the first model selected, but the analyses show it to be a very good model still. The other models all rotated positions since each model has strengths and weaknesses in their prediction abilities.

Real Pallet Scenario

Analysis was conducted by developing and running scenarios using TACCSAS. Initially, it is most important to run the system and observe how similar the results are when using the real

pallet data with the real airlift schedule and the cargo loading algorithm compared to the actual statistics collected from that month's GATES data. This provides further system validation and shows any initial process improvement by using the cargo algorithm versus the current loading methods. Figure 18 and Figure 19 show the number of stons of cargo and pallets shipped by using real data within the simulation and by simulating the pallet data compared to the actual shipping values. The red (actual), green (real data simulation), and the purple (Monte Carlo simulation) lines all run very close together. It also appears, by the position of the blue line (total cargo or pallets available), that each month has residual cargo. Residual cargo must either be factored into the next month's forecast for any additional aircraft purchases or placed on enroute channel missions. The simulation shows that the planners appear to load the aircraft well each month.

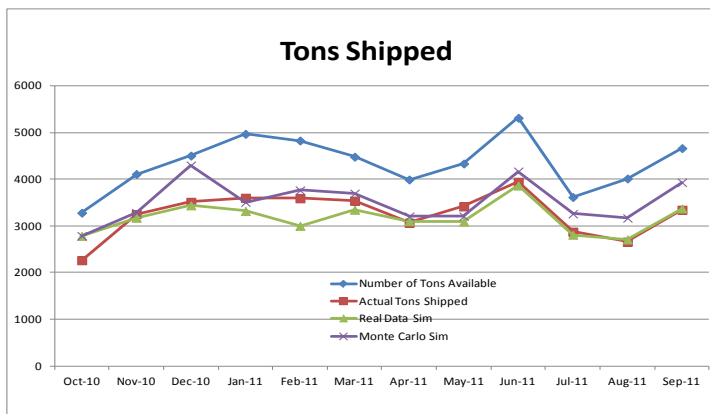


Figure 18 Actual Schedule Simulation (Cargo)

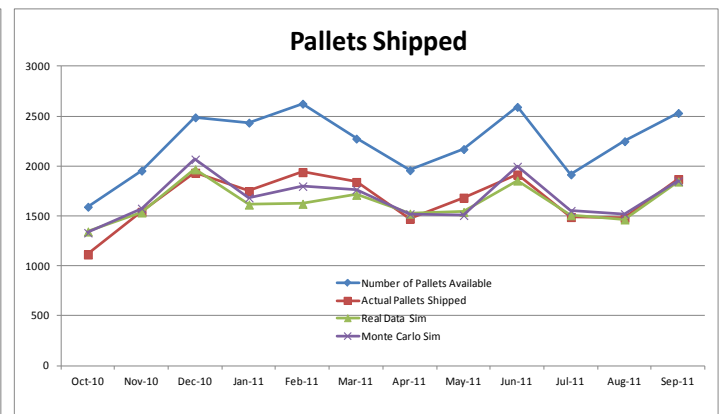


Figure 19 Actual Schedule Simulation (Pallets)

Readers may notice the large deviation of the real data simulation from the actual values on the data point “Feb-11.” This occurs because the simulation uses a higher minimum capacity of 75% on the amount of tonnage or the number of pallets on the aircraft before departure is allowed. The constraint is put into place due to current plans allowing planes to depart once they are 50% full (Figure 1); and actual data shows that planes depart with even lower utilization

rates. Increasing utilization rates reduces the number of aircraft necessary. For the mentioned data point, there were many days at the end of the month where these constraints were not met and airlift not scheduled, causing pallets to be left in inventory at the end of the simulation. If aircraft can take off with lower capacities, then more partially full flights are scheduled. The problem is determining the best percentage capacity to use.

The tonnage and the pallet values that are used as the maximum carrying capacities are planning values. The aircraft can carry more and in many cases, the additional ability is used. The tonnage utilization from a full year of actual data is between 40% and 125%. The aircraft are not capable of carrying more pallets than the set number of pallet positions built into an airframe.

After comparing the actual statistics and the simulation results, we can refer to the original schedule and determine where to make improvements. For “Oct-10,” 1,594 pallets needed to be shipped totaling 3,279.44 tons. The remaining pallets are either rolled over to the next month or transferred on enroute missions. Nearly all of the pallets can be airlifted with the “extra” CRAF. This means that the additional CRAF can be used if placed elsewhere in the schedule. When comparing the actual schedule to the schedule the simulation produces, on the few days where more than two CRAF are scheduled (instances of 3, 4, and 5 CRAF on a single day), the additional CRAF are usually cancelled. There are flights scheduled for every day in the actual schedule, and it would be an easy adjustment to ensure that there is an even distribution of departures across the month. This would lead to less cancellations and actually using the aircraft that are purchased.

Redistributed Scenario

To analyze this conjecture, a simulation is run with a schedule consisting of the same aircraft, with the same APOD, scheduled on different days. Figure 20 and Figure 21 show that there are no significant differences if the same flights are rescheduled. However, Figure 22 shows that a modified schedule allows the same pallets to ship the same month while consistently using less aircraft than the original schedule. After reviewing this study it is apparent that cancellations are easy to generate, but the important consideration is how to better schedule the flights to better accomplish the mission.

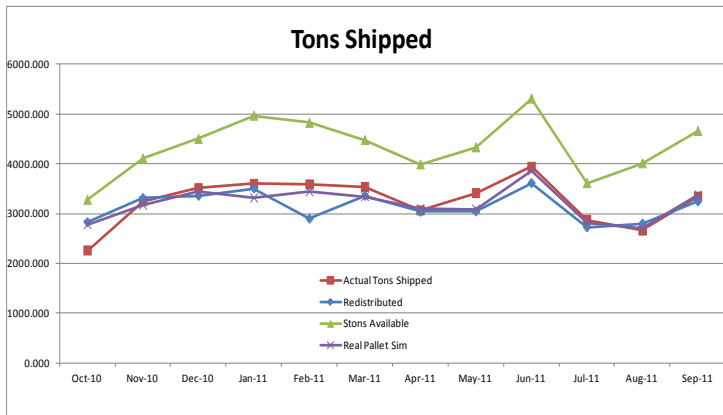


Figure 20 Redistributed Simulation (Cargo)

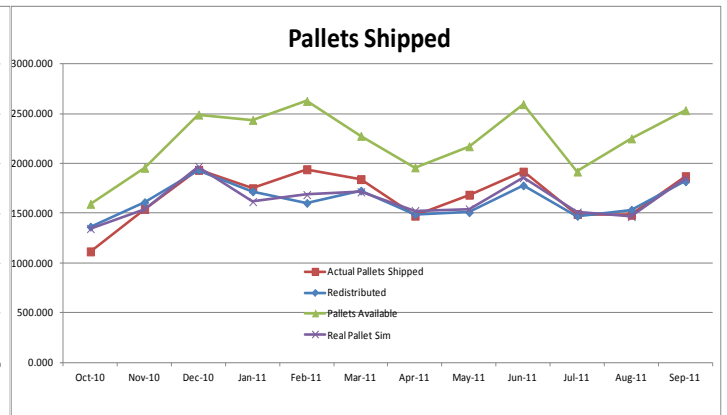


Figure 21 Redistributed Simulation (Pallets)

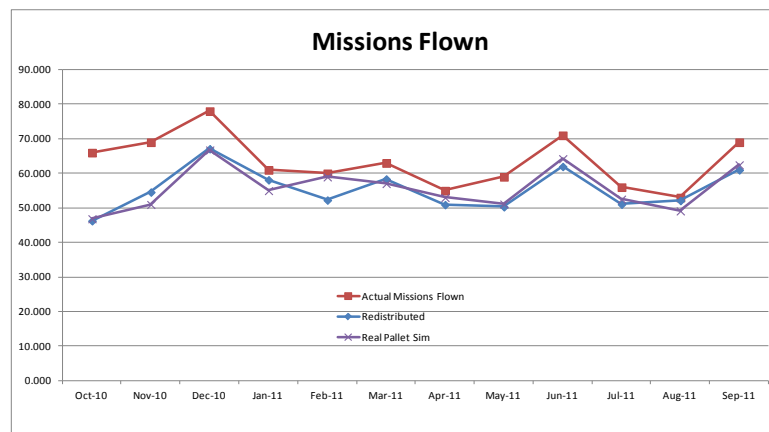


Figure 22 Redistributed Simulation (Missions Flown)

Times Series Model Scenarios

The forecasted weight and the cargo loading algorithm can be used to simulate what the potential schedule and airlift capabilities would look like for the upcoming months. As more data is included into the forecasting model, in most cases, a better fitting model is developed and the predictions improve. In repeated testing, some model instances show greater than 99% accuracy. The simulation shows planners how many aircraft they need to move a predicted number of pallets and a predicted number of tons.

The predicted pallet numbers are derived from the forecasted cargo weight. The mean of a previous month's pallet weights is found and the forecasted tons are divided by the mean pallet

weight to get the forecasted number of pallets. The pallet weight is then simulated as a random value using the normal distribution. The average weight of the simulated pallets is then very close to the actual pallet weight, providing additional validation to the simulation construction. Even if the forecasted value is lower, planners are still aware of how all of the predicted pallets are moved in the simulation. For example if it took about 33 aircraft to airlift over 3,000 tons, then it would be fair to say they would need an additional 16 aircraft to move an extra 1,500 tons.

The forecasted tonnage from the three previously identified models are used in the simulation to simulate how the potential pallet numbers and weights can be distributed amongst a predetermined airlift schedule with specified aircraft already assigned to days of the month. The simulation is replicated and the run results averaged. Figure 23 shows the forecasted cargo demand from the three models in relation to the actual cargo shipped during FY11. The forecasts appear to run across the minimum, maximum, and average actual values. Since the forecasts are so close to the actual shipping values, the results of the simulation show very similar charts across amount of cargo shipped and the number of pallets shipped. Figure 24 is a comparison of how many missions are flown in each month. It is expected that the two lower forecasts will require fewer missions, but the higher forecast (Intervention Model) also flies fewer missions to ship a slightly greater number of cargo pallets.

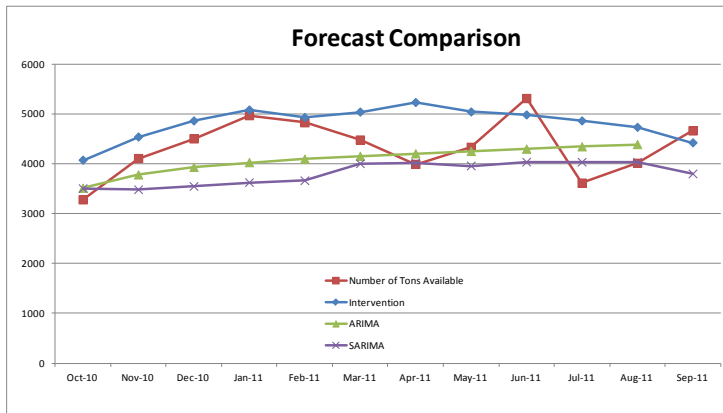


Figure 23 Forecasted Cargo Demand

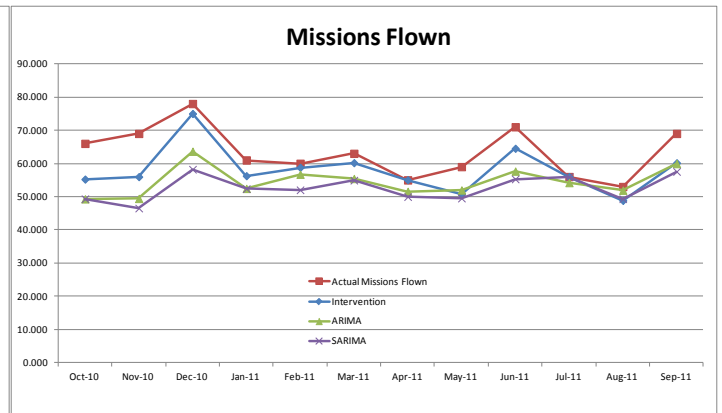


Figure 24 Forecast Simulation (Mission Flown)

Table 11 shows the minimum number of missions flown by each type of aircraft identified to transport the total tonnage of 3,241.86 stons as well as the average number of pallets flown on each type of aircraft for “Oct-11.” An important value in Table 11 is the total number of aircraft necessary to accommodate the forecasted number of tons or pallets. In this case, the intervention model forecasts that only 52 aircraft total or 36 CRAF are needed. When validated against the actual GATES data, the intervention model forecasted higher than the actual tonnage, but the simulation shows that the current schedule is capable of airlifting the actual number of pallets (1,594 pallets) and the full tonnage (3,279.44 tons) while still cancelling 13 CRAF. Although the forecast is higher than the actual value, CRAF can be cancelled and 42% of the cost saved.

	# missions	Tons/Msn	Tons Utilization	Pallets/Msn	Pallet Utilization
B74720	21.43	70.11	62.60%	32.74	99.20%
B74740	3.30	68.13	54.95%	32.23	97.65%
MD011F	8.39	70.69	83.16%	34.50	98.57%
B74710	2.71	67.61	86.68%	30.44	92.26%
C005M	1.00	60.27	98.80%	27.87	77.43%
C005B	5.15	59.65	97.78%	28.42	78.95%
C017A	9.47	39.11	86.91%	18.52	102.89%
	Total	Total	Average	Total	Average
Total/Avg	51.46	3241.86	75.43%	1529.70	96.86%

Avg Pallet Hold Time 2.77 days

Table 11 Intervention Model Simulation - Pallet Statistics “Oct-11”

Full Schedule Scenario

A simulation provides a great deal of flexibility in its modeling capabilities. It may be useful for planners to know how many aircraft are necessary or how many additional aircraft are needed to airlift every pallet if enroute missions are no longer available. The original schedules show that not enough aircraft are scheduled for flights to OAKN, leaving pallets in port. The schedules also show that CRAF are primarily scheduled for the first three weeks and not evenly scheduled through the end of the month. Table 12 shows the modified daily airlift schedule for each month.

Aircraft	Type	APOD
C017A	Organic	OAKN
C005A	Organic	OAKN
C005B	Organic	OAKN
B74710	CRAF	OAIX
B74720	CRAF	OAIX
B74740	CRAF	OAIX
MD011F	CRAF	OAIX
B74710	CRAF	OAKB
B74720	CRAF	OAKB
B74740	CRAF	OAKB
MD011F	CRAF	OAKB

Table 12 Full Daily Schedule

Figure 25 and Figure 26 show that it is possible to move every pallet available. February is still the outlier due to the capacity constraint. Figure 27 shows that a small increase in the number of monthly missions is enough to accommodate the pallet inventory. It is equal to approximately an additional 15 flights per month or 8 CRAF.

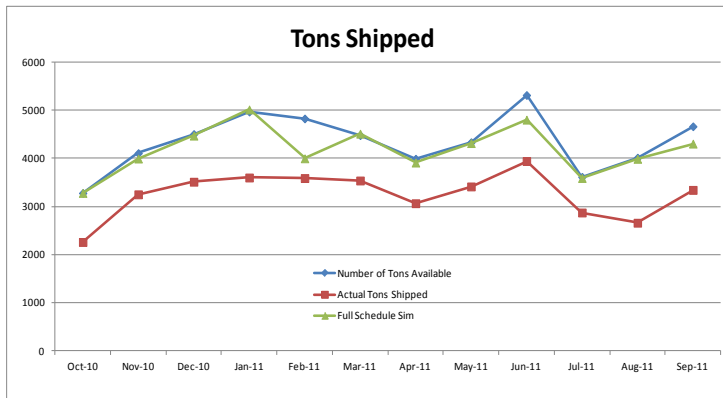


Figure 25 Full Simulation (Cargo)

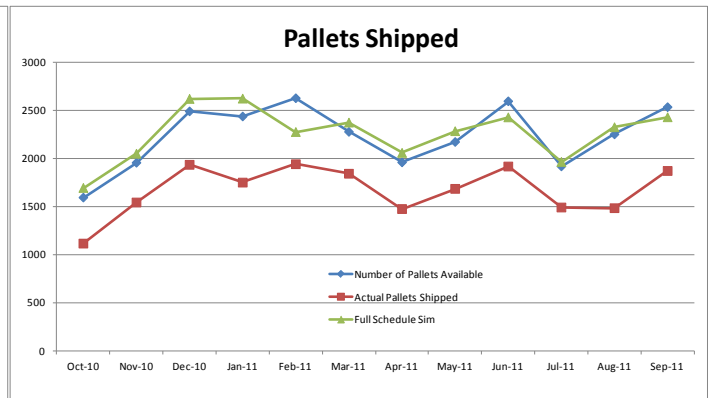


Figure 26 Full Simulation (Pallets)

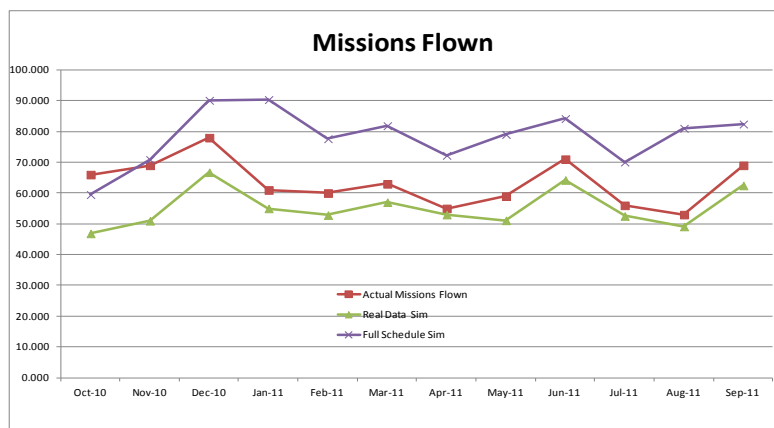


Figure 27 Full Simulation (Missions Flown)

All Organic Scenario

Planners can attempt to replicate all of their airlift efforts with just organic aircraft. If there is ever a situation where APODs are too hostile for CRAF aircraft, it might be useful to know how many missions organic aircraft would have to fly in order to fill the gaps. To run this scenario, each CRAF flight on the schedule is replaced with a similarly sized organic aircraft. Although C-5s are capable of carrying a great deal of cargo, the planning parameters for stons carried are quite low causing them to reach their maximum stons capacity before reaching their pallet capacity. Figure 30 shows that the same number of missions are used to move less cargo

as shown in Figure 28 and Figure 29. More organic aircraft would be required to perform the same amount of work, which may not be feasible due to the size of the organic aircraft inventory.

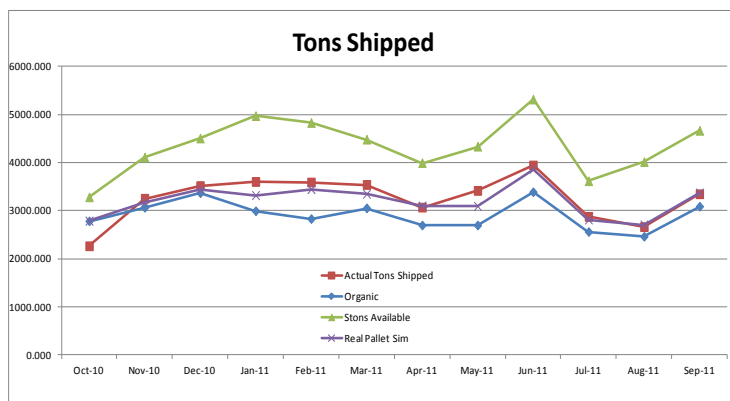


Figure 28 Organic Simulation (Cargo)

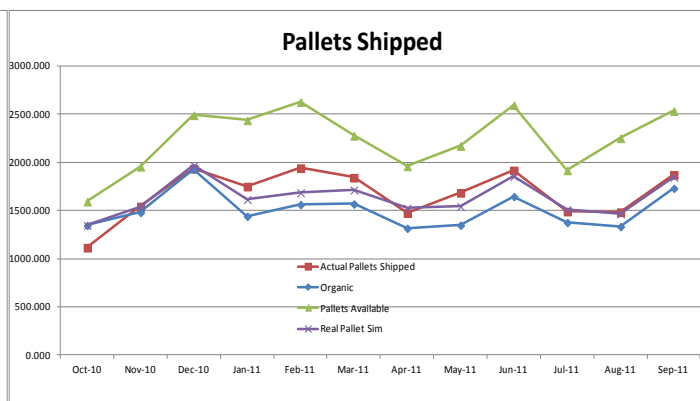


Figure 29 Organic Simulation (Pallets)

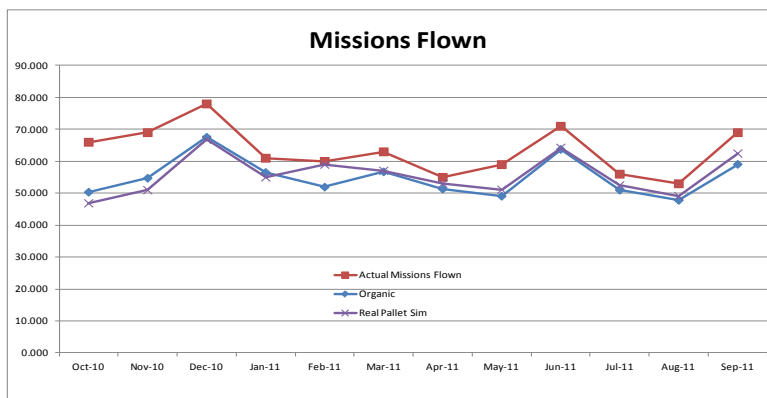


Figure 30 Organic Simulation (Missions Flown)

Results

Table 13 is a summary table of the scenario airlift mission number results compared to the actual data. With exception to the Full Schedule and Organic scenarios, each simulation scenario uses less CRAF aircraft to airlift the same number of pallets or cargo stons.

		Actual		Full		Real Pallet		Monte Carlo		Redistributed		Organic	
CRAF	B74710	14	484	14.207	581.77	10	444.49	7.0936	448.21	6.9211	443.55	0	0
	B74720	292		351.44		268.52		272.23		274.21		0	
	B74730	3		0		3		3.1		3		0	
	B74740	80		174		73.468		74.16		68.475		0	
	MD011F	95		42.118		89.5		91.624		90.95		0	
Organic	C005A	21	272	9.9	355.93	14	216.09	17.249	240.1	13.976	220.68	272	665.64
	C005B	60		69.102		46.745		50.049		44.857		156.01	
	C005M	14		0		11.229		13.142		12.451		83.081	
	C017A	176		276.93		143.12		158.66		148.39		153.54	
	KC010A	1		0		1		1		1		1	
Total		756	937.7	660.58	688.31	664.23	665.64						

Table 13 Scenario Summary - Total Airlift Missions

Table 15 is a summary of the monthly cost of schedules associated with each scenario.

The number of CRAF aircraft necessary for each scenario is shown along with the number of cancellations possible. Cost savings is calculated as previously discussed to include the sunk cost to schedule. If the number of CRAF flights scheduled is less than the actual number, cancellations are calculated. Simulation of each of the scenarios shows improvements can be made in nearly every month to achieve a more cost effective schedule. The redistributed schedule shows the most number of cancellations and therefore the greatest savings.

		Actual GATES	Full Schedule Sim	Real Pallet Sim	Monte Carlo Sim	Redistributed
Oct-10	CRAF Flights	49	40	30	29	34
	Cancellations		8	18	19	15
	Cost of Schedule	\$ 22,540,000.00	\$ 19,295,431.75	\$ 15,646,000.00	\$ 15,398,316.67	\$ 17,058,550.79
Nov-10	CRAF Flights	41	44	32	33	33
	Cancellations		0	9	8	8
	Cost of Schedule	\$ 18,860,000.00	\$ 20,240,000.00	\$ 15,620,000.00	\$ 15,980,000.00	\$ 15,755,019.84
Dec-10	CRAF Flights	42	55	41	41	40
	Cancellations		0	0	0	2
	Cost of Schedule	\$ 19,320,000.00	\$ 25,354,360.32	\$ 18,884,022.22	\$ 18,961,747.62	\$ 18,372,774.60
Jan-11	CRAF Flights	36	51	36	36	36
	Cancellations		0	0	0	0
	Cost of Schedule	\$ 16,560,000.00	\$ 23,460,000.00	\$ 16,560,000.00	\$ 16,560,000.00	\$ 16,780,197.62
Feb-11	CRAF Flights	43	49	42	44	40
	Cancellations		0	1	0	3
	Cost of Schedule	\$ 19,780,000.00	\$ 22,540,000.00	\$ 19,296,511.90	\$ 20,420,769.05	\$ 18,501,579.37
Mar-11	CRAF Flights	43	49	41	42	41
	Cancellations		0	1	1	1
	Cost of Schedule	\$ 19,780,000.00	\$ 22,562,032.54	\$ 19,119,065.08	\$ 19,229,227.78	\$ 19,097,707.94
Apr-11	CRAF Flights	34	45	36	35	36
	Cancellations		0	0	0	0
	Cost of Schedule	\$ 15,640,000.00	\$ 20,484,073.81	\$ 16,468,638.89	\$ 16,120,207.14	\$ 16,464,659.52
May-11	CRAF Flights	37	48	33	33	35
	Cancellations		0	3	4	2
	Cost of Schedule	\$ 17,020,000.00	\$ 22,013,099.21	\$ 15,691,107.14	\$ 15,395,561.90	\$ 16,125,163.49
Jun-11	CRAF Flights	45	51	43	45	41
	Cancellations		0	1	0	4
	Cost of Schedule	\$ 20,700,000.00	\$ 23,460,000.00	\$ 19,908,896.03	\$ 20,789,170.63	\$ 19,235,010.32
Jul-11	CRAF Flights	33	42	33	33	32
	Cancellations		0	0	0	1
	Cost of Schedule	\$ 15,180,000.00	\$ 19,324,600.00	\$ 15,053,773.81	\$ 15,084,440.48	\$ 14,820,000.00
Aug-11	CRAF Flights	35	48	34	34	35
	Cancellations		0	1	0	0
	Cost of Schedule	\$ 16,100,000.00	\$ 22,080,000.00	\$ 15,740,000.00	\$ 15,786,159.52	\$ 16,100,000.00
Sep-11	CRAF Flights	46	54	43	43	42
	Cancellations		0	2	3	3
	Cost of Schedule	\$ 21,160,000.00	\$ 24,840,000.00	\$ 20,045,860.32	\$ 19,995,411.11	\$ 19,624,600.00
Total Cancellations			8	36	35	39
Total Cost		\$ 222,640,000.00	\$ 265,653,597.62	\$ 208,033,875.40	\$ 209,721,011.90	\$ 207,935,263.49
Total Savings			\$ (43,013,597.62)	\$ 14,606,124.60	\$ 12,918,988.10	\$ 14,704,736.51

Table 14 Scenario Comparison of Cost Savings

Summary

Continuous one-step ahead forecasting with the five models selected shows there are various models capable of providing regular accurate forecasts. Having an actual forecasting

ability is substantial in terms of reserving CRAF. Rather than providing weak forecasts and under-committing on the “fixed buy,” planners can provide much greater commitment and incentive to the CRAF participants and the short term buy. Planners may reduce the number of CRAF they over-purchase by applying the forecast to the simulation. The simulation easily displays how to move the forecasted pallets with the least number of aircraft possible, allowing schedulers to examine any shortcomings. With just a few examples, it is easy to show that the simulation can provide different options by changing a few simple parameters. The take away from the simulation is that there is money to be saved in the current scheduling whether it is a matter of reducing the number of CRAF performing these channel missions or reducing the number of CRAF flying enroute missions. It is feasible to conduct a full organic schedule, especially if wartime ACL parameters are being used, but not necessarily preferred.

V. Conclusion

This research builds upon the foundation for a potential forecasting tool and a cargo loading simulation. Time series forecasting provides an accurate method for predicting cargo demand and while a “best” model may not be consistent with every new forecast generated, the forecasts are still quite accurate. The goal of continued forecasting research is to determine if advanced time series models can be applied to generate more accurate forecasts. The development of new models leads to the additional question of whether or not forecasts and simulation can lead to accurate airlift schedules with the objective to maximize airlifted cargo tons. The suggested models, the capabilities, the potential impacts, and areas for improvement or future investigation are presented below.

Results

This research provides a brief overview of the current airlift results and continues with a detailed examination of how and where improvements can be made. Two past research projects provide a strong foundation for thesis (DeYoung, 2012; Lindstrom, 2012). This research focuses on incorporating mathematical models into a long standing planning process, how to apply the models for reliable results, and how to generate an increasingly accurate outlook from 12 months out to 1 month out. The techniques utilized in this process, time series forecasting, Monte Carlo simulation, and heuristic optimization, each offer individual benefits towards increasing value and efficiency.

Forecasting models are constructed having high R^2 values and strong goodness-of-fit criteria to create accurate forecasts for short term and long-term cargo demand. The models are validated by using data splitting. The MSEs are compared amongst multiple models through monthly forecast iterations for a full year to observe how the models handled new data and

reacted to the changes. This research demonstrates that forecasting can be a very useful tool and can easily fit a cargo data set. There are a variety of models applied to the data set with good results, and each can be updated regularly as new data are received to improve model predictive capabilities.

The Monte Carlo simulation produces very good estimates of cargo pallet weight by using simple distributions and good samples of pallet arrivals and destinations with discrete probability distributions. The cargo loading algorithm effectively and efficiently loads aircraft with pallets, paired by destinations, and shows cost savings and areas for modification. The algorithm is validated through data splitting and the results showed the same cargo movement performance can be achieved with far less aircraft and large savings. The simulation is easily used to generate potential schedules and show related statistics allowing planners to make changes or improvements or to plan ahead.

Past research emphasized the need for forecasting airlift sustainment cargo demand for the AORs (DeYoung, 2012) which is why Afghanistan is the focus. While this is the main basis of the research, simulations show there is room for improvement in the overall scheduling of airlift, the loading of aircraft, and the understanding of cancellation fees and port hold time. If these issues exist outside of planning for the AOR, then it would be beneficial to explore applications to other aerial ports as well.

Research Conclusion

The model forecast charts in Appendix C show that with time, forecasts can sometimes become less accurate. A use of these charts is whether or not the forecasts are an improvement over the current moving average model used. The improvement shown provides a direct benefit to the DoD's incentive relationship with its CRAF partners. A more accurate projection of

CRAF business one year out can confidently increase the size of the “fixed buy” and reduce the size of “expansion buys” The methods that are used in this research are easily applied and the goodness-of-fit is directly dependent on how planners choose to filter the input data.

This research found no past research that applies simulation to such a broad planning effort. Most simulation models or products appear to be applied to the physical loading of the aircraft or for cargo routing/deliveries. The benefit of simulation is that it can be tailored to the need and its performance can be validated with real data sets. The forecasts and the simulation focus on improved planning overall and show potential financial impacts or savings from the airlift schedule used. The focus of the simulation is improving the planning process to reduce costs. This includes the cost benefit of cancelling previously scheduled missions as well. The main conclusion derived from analyzing data from FY2011 is that scheduling of airlift needs improvement and depending on how the application of these methods continue, there are potential cost savings in reducing the number of CRAF flying each month and cancelling unnecessary CRAF.

A direct result of the research is a modeling tool that incorporates the techniques from Chapters 3 and 4. This Excel model forecasts cargo demand using multiple models, uses the forecasted demand to simulate a schedule of aircraft for that month based on an input schedule or a sample schedule, and provides results of the simulation showing areas of improvement and potential cost impacts or savings. Users can include aircraft of their choosing, schedule aircraft as they please, use multiple statistical distributions to simulate pallet weights and review how each individual aircraft is loaded. This tool can improve USTRANSCOMs current planning capabilities.

Recommendations

USTRANSCOM planners should begin to use forecasting techniques in their airlift planning. Multiple models can be applied repeatedly on a monthly basis while injecting new data and comparing it with actual cargo data. It is also recommended that weekly data be used and tested for a six week forecast to incorporate last minute changes. Multiple models should be applied due to the nature of the model types and the real data set, but this research shows that using these models is beneficial. Side-by-side comparisons for a time period provide planners an evaluation period as well as a learning period. Assuming TACCSAS performs well, it is an adaptive system ready to incorporate new data and simulate real schedules and efficiencies based off of the forecasted demand. It is recommended that TACCSAS be used as soon as possible to evaluate current schedules and for future planning.

Future Research

Due to the difficulty in retrieving BOG data as well as the observation that BOG dependent forecasting models did not provide improved forecasts, future models should be developed using just cargo demand. Using the one time series will also simplify future model development. In addition to using a single input, past research (DeYoung, 2012) shows that weekly demand values can be used to generate accurate forecasts as well. Actual application may require a combination of both monthly and weekly forecasts in order to enhance current planning efforts.

The simulation can easily be applied to other APODs and other APOEs to determine if modifications can be made to their airlift scheduling. For example, all Dover AFB data can be replaced with that from Travis AFB to determine if savings are available in PACAF missions or if schedules can be performed in a manner to provide better coverage and more airlift.

While there are a number of advanced forecasting techniques, artificial neural networks (ANN) in particular are quite accurate and are a black box system that can “learn” nearly any data set. It may be worth the time and the effort to apply ANNs to the time series data to potentially derive a more accurate forecast. Additional software or add-ins are necessary to perform the computations, but many of these solutions are readily available and fairly straightforward in their use (with some understanding of the topic). A brief experimentation is performed with the same set of time series cargo data and time-delay neural networks to observe the performance. Recurrent neural networks are also applied to the data series. The steps and the results are found in Appendix F.

WORKS CITED

- 618th Tanker Airlift Control Center*. (2008, December 29). Retrieved from Air Mobility Command: <http://www.amc.af.mil/library/factsheets/factsheet.asp?id=239>
- (2005). Air Cargo Tonnage Forecast and Capacity Analysis. In W. S. Associates, *Florida Air Cargo System Plan - Task 3*. Florida: Wilbur Smith Associates.
- Air Mobility Planning Factor. (2011, December 12). *Air Force Pamphlet 10-1403*.
- AMC/A3CF, H. (2012, November 1). MAF MISSION ID ENCODE/DECODE PROCEDURES. Air Mobility Command.
- Andreoni, A., & Postorino, M. N. (2006). A Multivariate Model to Forecast Air Transport Demand. *European Transport Conference*. Association for European Transport and Contributors 2006.
- Arthur, D. (2007). *Issues Regarding the Current and Future Use of the Civil*. National Security Division. Congressional Budget Office.
- Barreto, H., & Howland, F. M. (2006). Introductory Econometrics.
- Belasco, A. (2011). *The Cost of Iraq, Afghanistan, and Other Global War on Terror Operations Since 9/11*. Congressional Research Service.
- Borseth, A., Hwang, J., Solis, W., La Due Lake, R., Marchand, G., Perdue, C., . . . Woods, S. (2010). *Defense Transportation: Additional Information Is Needed for DOD's Mobility Capabilities and Requirements Study 2016 to Fully Address All of Its Study Objectives*. U.S. Government Accountability Office, Washington, DC.
- Bowerman, B. L., O'Connell, R. T., & Koehler, A. B. (2005). *Forecasting, Time Series, and Regression: An Applied Approach* (4th ed.). Belmont, CA: Thomson Brooks/Cole.

- Chamber, J. C., Mullick, S. K., & Smith, D. D. (1971, July-August). How to choose the right forecasting technique. *Harvard Business Review*, 45-74.
- Chien, C.-F., Chen, Y.-J., & Peng, J.-T. (2008). Demand Forecast of Semiconductor Products Based on Technology Diffusion. *Proceedings of the 2008 Winter Simulation Conference*, 2313-2322.
- Datamonitor. (2011). *FedEx Corporation*. New York: datamonitor.com.
- DeYoung, D. S. (2012). *Time Series Forecasting of Airlift Sustainment Cargo Demand*. Air Force Institute of Technology, Department of Operational Sciences. Wright-Patterson Air Force Base: Air University.
- Dobbs, C. O., & Keller, M. J. (1999). Commercial Communications Analogy to Civil Reserve Air Fleet (CRAF). *IEEE*, 1495-14999.
- Ediger, V., & Akar, S. (2007). ARIMA forecasting of primary energy demand by fuel in Turkey. *Energy Policy*, 35, 1701-1708.
- Heng, H.-j., Zheng, B.-z., & Li, Y.-j. (2009). Study of SVM-Based Air-Cargo Demand Forecast Model. *2009 International Conference on Computational Intelligence and Security*, 53-55.
- House of Representative Hearing, 111 Congress. (2009, May 13). *The Economic Viability of the Civil Reserve Air Fleet (CRAF) Program*. U.S. Government Printing Office.
- JMP 10. (2012). *JMP 10.0.1 [Computer Software]*. Cary, North Carolina: SAS Institute Inc.
- Knight, W., & Bolkcom, C. (2008). *Civil Reserve Air Fleet (CRAF)*. Foreign Affairs, Defense, and Trade Division. Congressional Research Service.

- Lindstrom, C. D. (2012). *Examining the Value of Advanced Notification of Cargo Generation For Scheduling Channel Airlift Missions*. Air Force Institute of Technology, Department of Operational Sciences. Wright-Patterson Air Force Base: Air University.
- Liu, P., Chen, S.-H., Yang, H.-H., Hung, C.-T., & Tsai, M.-R. (2008). Application of Artificial Neural Network and SARIMA in Portland Cement Supply Chain to Forecast Demand. *Fourth International Conference on Natural Computation*, 97-101.
- (n.d.). Metaheuristics. In F. S. Hillier, & G. J. Lieberman, *Introduction to Operations Research* (Eighth ed., pp. 617-653). New York: McGraw-Hill.
- Michael W. Grismer, J. (2011). Transforming the Civil Reserve Air Fleet. *Joint Forces Quarterly*, 4th Quarter(63), 8.
- Microsoft. (2007). *Microsoft Excel [Computer Software]*. Redmond, Washington: Microsoft.
- Mobility. (2012, October 15). *Defense Transportation Regulation - Part III*.
- Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2008). *Introduction to Time Series Analysis and Forecasting*. Hoboken, New Jersey: John Wiley & Sons.
- Second Line of Defense. (2011). *The Tanker Airlift Control Center (TACC)*.
- Solis, W., Borseth, A., Brown, R., Hawk, J., Hubbard, J. R., Jones, M., . . . Woods, S. (2009). *DOD Should Take Steps to Strengthen Management*. Washington, DC: Government Accountability Office.
- TranSystems. (2010). *Air Cargo Mode Choice and Demand Study*. State of California, Department of Transportation. TranSystems.
- USTRANSCOM History. (2012, February 8). Retrieved from U.S. Transportation Command: <http://www.transcom.mil/about/summary.cfm>

Westcott, M. (2006, September 1). *<https://acc.dau.mil/CommunityBrowser.aspx?id=113806>*.

Retrieved from www.transcom.mil: <http://www.transcom.mil/news/read.cfm?id=6863>

Appendices

Appendix A

The time series of the monthly total of the cargo weights can be reviewed in the table below. Cargo numbers are pulled from the GATES database and manually sorted and calculated. Boots of the Ground values are taken from (Belasco, 2011). For the model development, the last estimated value of 98,000 BOG was used for FY2011.

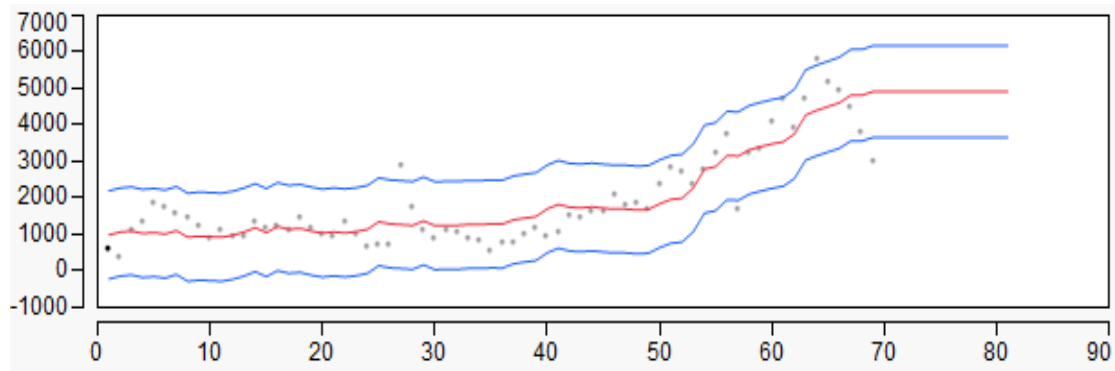
Date	Tons of Cargo	BOG	Date	Tons of Cargo	BOG
Jan-05	626.24	18,700	Oct-08	2,083.65	33,000
Feb-05	355.21	20,300	Nov-08	1,796.79	33,000
Mar-05	1098.62	20,900	Dec-08	1,848.90	32,500
Apr-05	1321.85	19,500	Jan-09	1,709.50	32,800
May-05	1868.07	20,000	Feb-09	2,395.76	35,900
Jun-05	1765.68	19,200	Mar-09	2,814.97	38,350
Jul-05	1564.97	21,100	Apr-09	2,710.91	39,000
Aug-05	1464.06	17,400	May-09	2,397.15	44,700
Sep-05	1239.89	18,000	Jun-09	2,784.60	55,100
Oct-05	888.69	17,800	Jul-09	3,240.28	56,500
Nov-05	1141.64	17,400	Aug-09	3,761.82	62,600
Dec-05	965.61	18,500	Sep-09	1,684.92	62,300
Jan-06	968.55	20,300	Oct-09	3,129.91	65,800
Feb-06	1317.77	22,700	Nov-09	3,240.86	67,500
Mar-06	1171.79	20,000	Dec-09	4,015.49	69,000
Apr-06	1246.90	23,300	Jan-10	4,669.42	70,200
May-06	1123.86	21,800	Feb-10	3,820.45	74,600
Jun-06	1430.04	22,300	Mar-10	4,551.66	85,000
Jul-06	1166.78	20,800	Apr-10	5,605.41	87,600
Aug-06	1013.93	19,700	May-10	5,152.41	89,700
Sep-06	970.40	20,400	Jun-10	4,962.08	91,775
Oct-06	1340.10	19,800	Jul-10	4,393.06	95,925
Nov-06	972.08	20,500	Aug-10	3,762.09	95,920
Dec-06	664.56	21,800	Sep-10	2,974.05	98,000
Jan-07	701.91	26,000	Oct-10	3,300.60	
Feb-07	728.49	24,800	Nov-10	4,149.92	
Mar-07	2897.11	24,400	Dec-10	4,536.60	
Apr-07	1742.49	23,900	Jan-11	5,069.22	
May-07	1111.17	26,400	Feb-11	4,852.68	
Jun-07	900.47	23,800	Mar-11	4,529.13	
Jul-07	1135.81	24,000	Apr-11	4,037.11	
Aug-07	1072.69	24,000	May-11	4,370.84	
Sep-07	873.20	24,500	Jun-11	5,318.32	
Oct-07	840.92	24,400	Jul-11	3,691.94	
Nov-07	550.83	24,800	Aug-11	4,014.77	
Dec-07	744.61	24,600	Sep-11	4,941.08	
Jan-08	756.80	27,000			
Feb-08	981.68	28,000			
Mar-08	1166.90	28,800			
Apr-08	920.68	33,100			
May-08	1028.56	35,600			
Jun-08	1539.14	34,000			
Jul-08	1469.30	33,700			
Aug-08	1623.82	34,200			
Sep-08	1611.04	33,500			

Appendix B

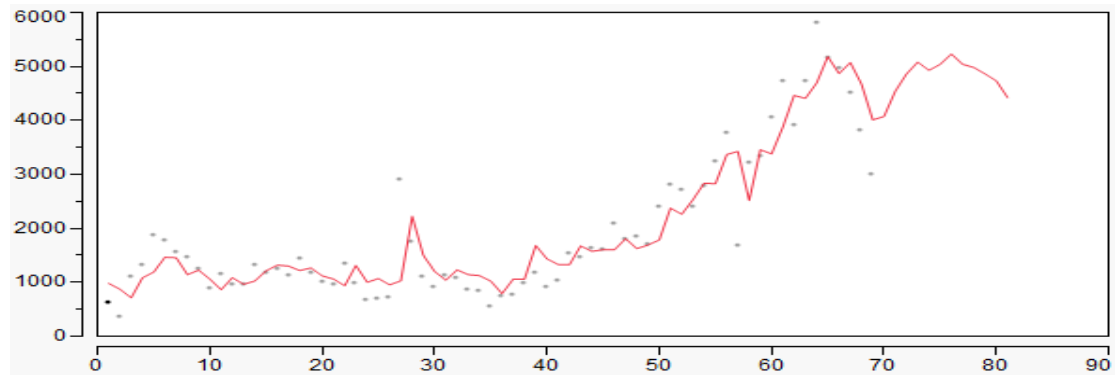
Monthly Afghanistan Cargo Demand Models

The following graphs show the monthly historical cargo time series (black dots) with the fitted forecasting model (red line). A 95% confidence interval is provided (blue lines) around the forecasted value.

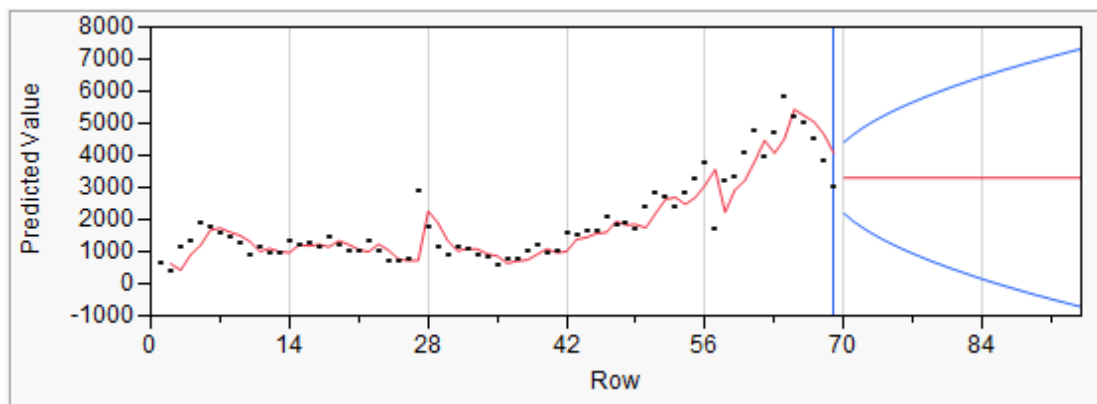
Figure 31 Monthly Forecast Model Graphs



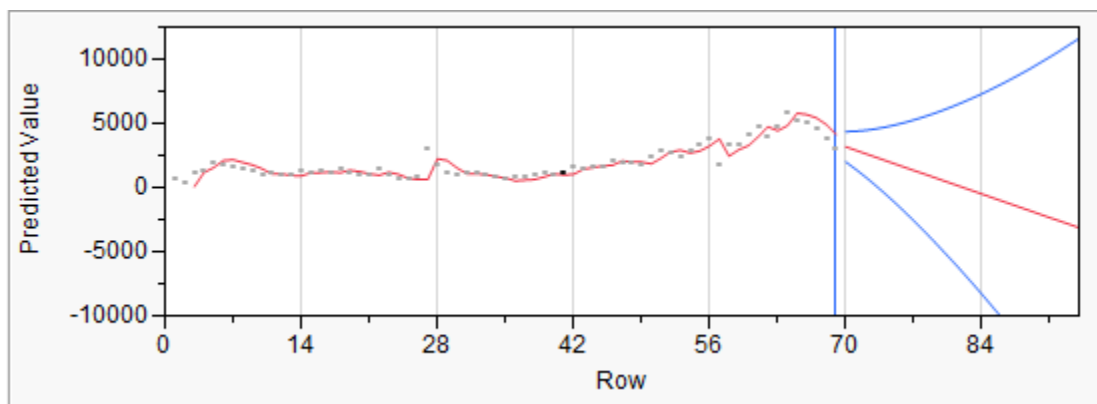
Linear Regression



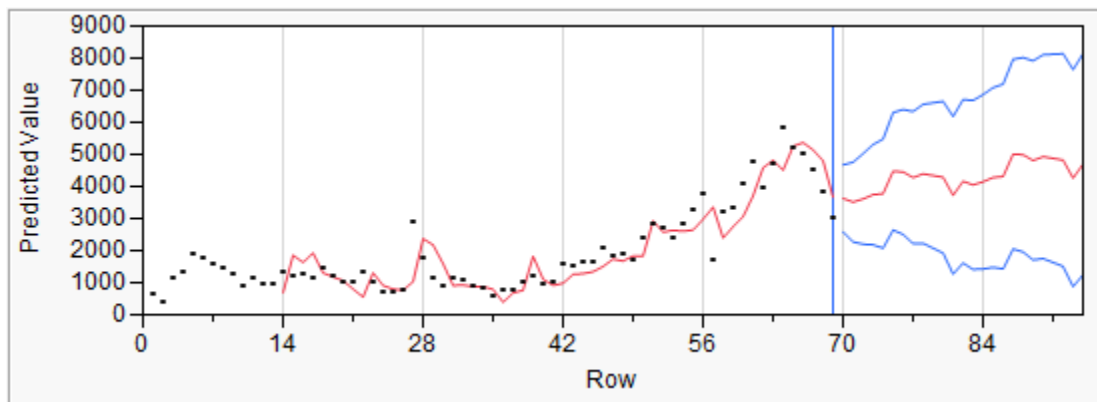
Intervention Model



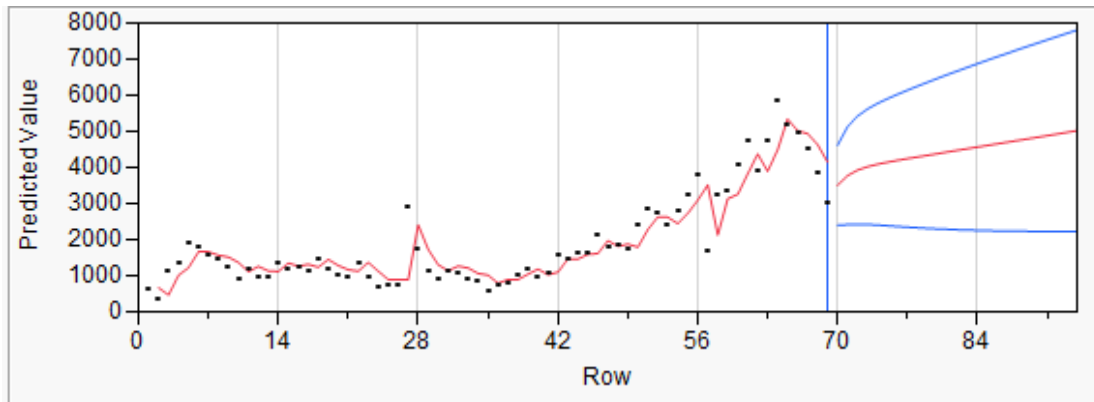
Simple Exponential Smoothing



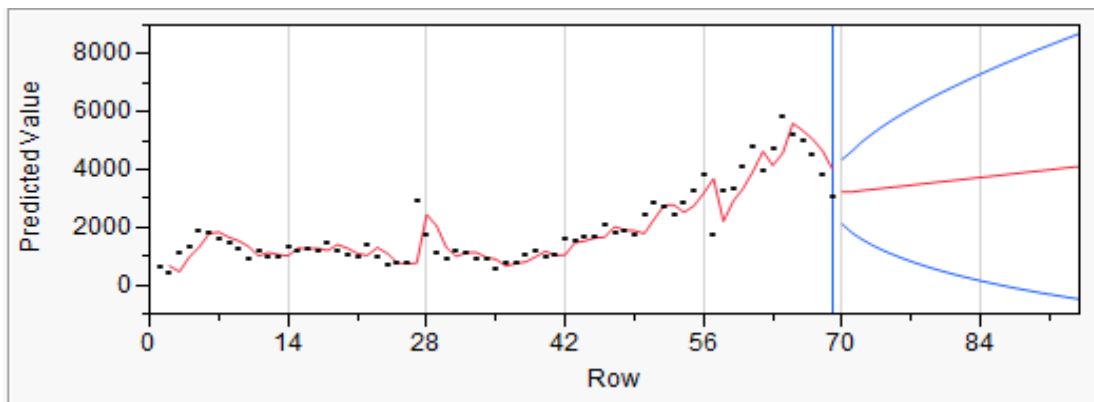
Double (Brown) Exponential Smoothing



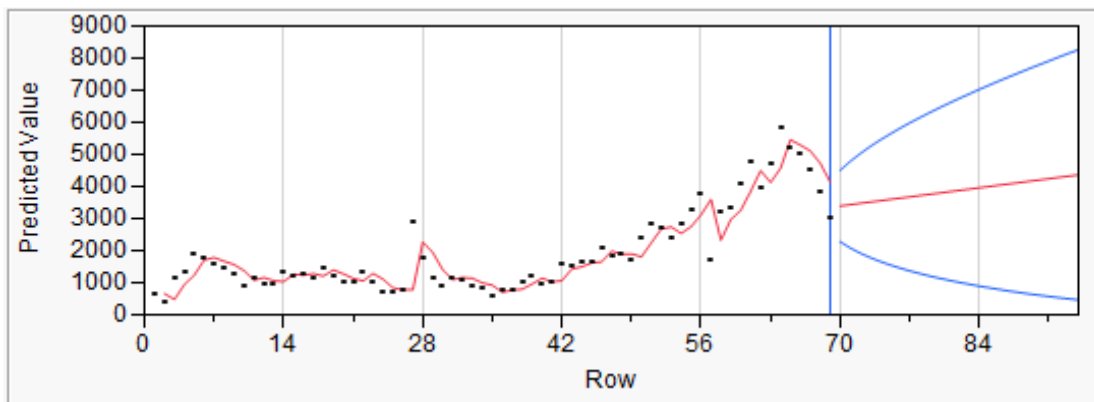
Seasonal Exponential Smoothing



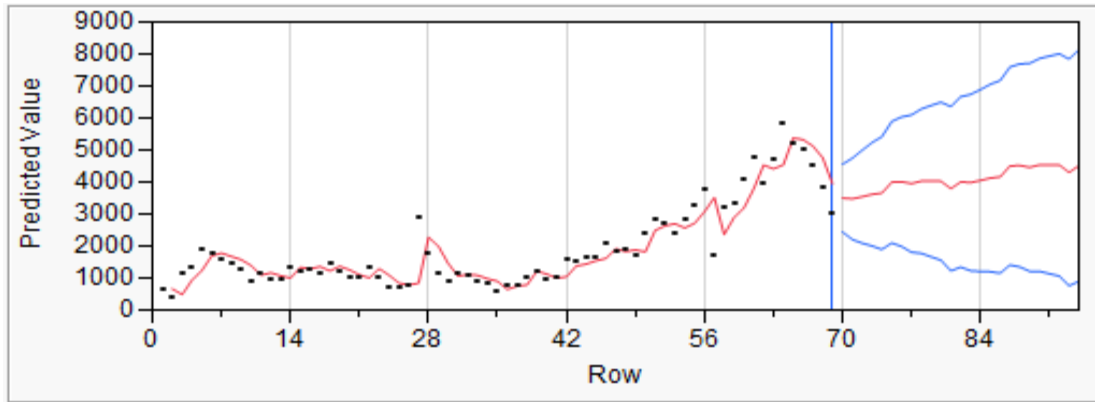
ARIMA(1,1,1)



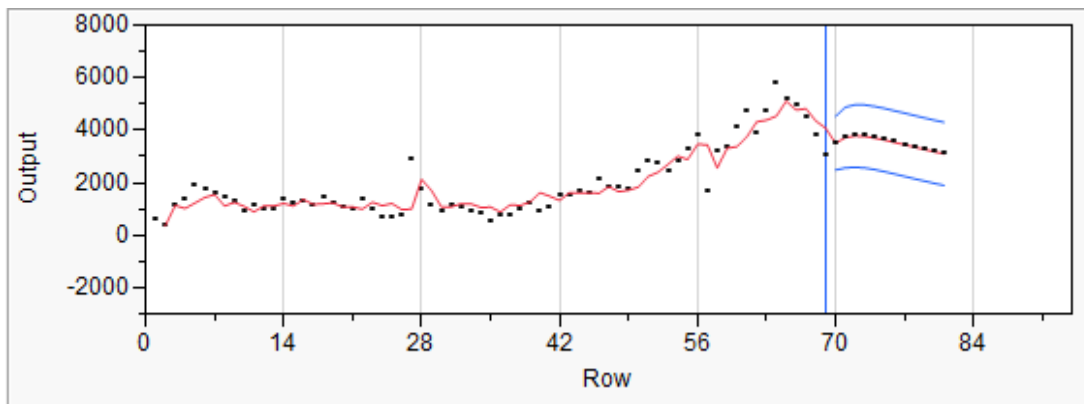
ARI(1,1)



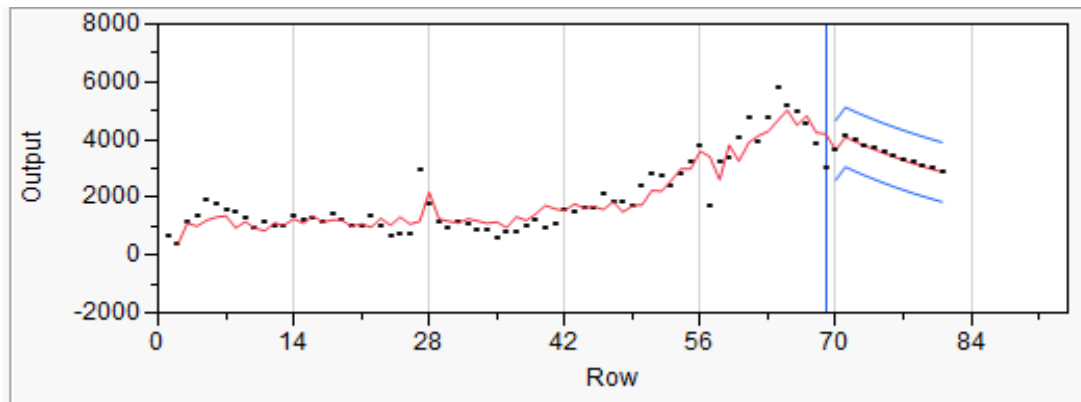
IMA(1,1)



SARIMA(0,1,1)(1,0,1)12



Transfer Function – Cargo (1,0,0)/BOG(0,1,1)



Transfer Function – Cargo (0,0,1)/BOG(0,1,1)

Appendix C

Top 5 Models Iterative Comparison

An iterative comparison performed with the five best models is shown in the figures below. An initial 12 month forecast was produced by each model and the overall accuracies are determined. A new data point was then included into the data set and new forecasts are generated for the remaining months. The purpose of this is to find out if these models are only good in an instance or if forecasting (and these models specifically) can be regularly applied to this type of data set. This process proved that these models are capable of accommodating change and continually predicting cargo tonnage on a yearly, quarterly, or monthly basis.

Table 15 All Model Residual and Percentage Deviations

		69 obs	70 obs	71 obs	72 obs	73 obs	74 obs	75 obs	76 obs	77 obs	78 obs	79 obs	80 obs
		12 Month	11 Month	10 Month	9 Month	8 Month	7 Month	6 Month	5 Month	4 Month	3 Month	2 Month	1 Month
Intervention Model	Month 70	-774.01											
	Month 71	-390.09	160.14										
	Month 72	-326.19	158.30	82.72									
	Month 73	-13.21	498.51	490.46	444.50								
	Month 74	-76.91	186.67	214.35	196.75	-85.54							
	Month 75	-511.58	-184.08	-137.62	-141.49	-291.32	-243.26						
	Month 76	-1195.10	-699.47	-643.18	-640.41	-729.19	-709.98	-557.09					
	Month 77	-671.52	-377.32	-315.92	-309.94	-370.57	-364.63	-285.80	71.44				
	Month 78	335.37	564.43	628.47	636.01	588.35	588.20	633.36	822.11	781.51			
	Month 79	-1171.06	-1064.78	-999.37	-991.08	-1032.76	-1035.71	-1005.86	-893.69	-909.55	-1401.93		
	Month 80	-719.24	-743.36	-677.25	-668.59	-707.51	-711.75	-688.86	-611.50	-616.04	-847.68	-49.90	
	Month 81	517.51	182.25	248.72	257.56	219.90	215.08	234.81	296.34	296.98	175.03	554.62	593.26
Seasonal Exponential Smoothing	Month 70	-335.09											
	Month 71	629.62	860.42										
	Month 72	916.64	1147.44	599.62									
	Month 73	1316.37	1547.54	999.18	606.05								
	Month 74	1068.84	1300.01	751.65	358.52	-68.77							
	Month 75	48.62	279.79	-268.57	-661.70	-1088.99	-1041.17						
	Month 76	-424.46	-193.30	-741.65	-1134.78	-1562.08	-1514.26	-823.88					
	Month 77	86.19	317.36	-231.00	-624.13	-1051.43	-1003.61	-313.23	308.84				
	Month 78	917.24	1148.41	600.05	206.92	-220.37	-172.56	517.82	1139.90	913.70			
	Month 79	-657.31	-426.15	-974.50	-1367.63	-1794.93	-1747.11	-1056.73	-434.66	-660.86	-1302.06		
	Month 80	-281.05	-49.88	-598.24	-991.37	-1418.67	-1370.85	-680.47	-58.40	-284.60	-925.80	-102.54	
	Month 81	1208.38	1439.55	891.19	498.06	70.77	118.59	808.97	1431.04	1204.84	563.64	1386.89	1452.17
ARIMA(1,1,1)	Month 70	-211.79											
	Month 71	370.11	534.57										
	Month 72	606.06	740.86	342.76									
	Month 73	1043.30	1160.74	829.52	576.18								
	Month 74	757.64	865.54	566.17	356.90	-70.70							
	Month 75	377.42	480.50	195.33	7.22	-342.51	-289.95						
	Month 76	-165.34	-64.36	-344.18	-522.73	-832.50	-789.59	-577.65					
	Month 77	120.44	220.87	-58.08	-232.92	-523.02	-485.14	-313.23	110.35				
	Month 78	1021.31	1122.05	841.73	667.62	386.34	421.69	573.47	916.83	835.59			
	Month 79	-651.05	-549.53	-832.35	-1007.21	-1285.48	-1251.31	-1109.24	-806.88	-872.74	-1478.45		
	Month 80	-373.90	-271.34	-557.24	-733.61	-1011.97	-978.24	-840.43	-558.26	-616.14	-1103.81	-80.33	
	Month 81	506.86	610.61	321.35	143.07	-137.04	-103.33	33.08	306.10	252.22	-175.91	636.24	692.50
IMA(1,1)	Month 70	-211.79											
	Month 71	370.11	783.80										
	Month 72	606.06	1131.05	590.67									
	Month 73	1043.30	1624.24	1076.29	656.26								
	Month 74	757.64	1368.27	812.75	386.77	-102.95							
	Month 75	377.42	1005.29	442.19	10.27	-486.27	-409.78						
	Month 76	-165.34	473.84	-96.82	-534.68	-1038.04	-960.50	-662.71					
	Month 77	120.44	768.14	189.90	-253.90	-764.07	-685.49	-383.70	109.72				
	Month 78	1021.31	1676.19	1090.38	640.63	123.65	203.28	509.07	1008.99	927.04			
	Month 79	-651.05	10.39	-583.00	-1038.69	-1562.49	-1481.81	-1172.02	-665.61	-748.61	-1425.30		
	Month 80	-373.90	293.79	-307.18	-768.80	-1299.42	-1217.69	-903.90	-390.99	-475.06	-1160.45	-207.32	
	Month 81	506.86	1180.66	572.13	104.56	-432.88	-350.10	-32.31	487.09	401.97	-292.13	673.36	815.47
SARIMA(0,1,1)(1,0,1)12	Month 70	-335.39											
	Month 71	59.24	815.86										
	Month 72	596.49	1138.31	591.76									
	Month 73	1272.19	1596.19	1046.59	586.53								
	Month 74	1191.59	1343.61	789.54	363.36	-32.72							
	Month 75	997.21	684.94	137.97	-229.82	-605.16	-581.62						
	Month 76	627.94	179.32	-373.00	-831.38	-1271.75	-1250.24	-846.32					
	Month 77	1078.29	570.42	10.00	-416.92	-847.76	-824.93	-435.59	183.49				
	Month 78	2136.59	1443.48	880.07	461.39	41.55	65.15	472.94	1079.98	944.21			
	Month 79	615.51	-181.73	-751.06	-1174.03	-1585.71	-1561.07	-1144.70	-556.59	-694.22	-1298.98		
	Month 80	1038.39	142.99	-432.29	-845.83	-1240.50	-1214.46	-786.79	-229.38	-368.83	-939.44	-39.64	

All Model Residuals

		69 obs	70 obs	71 obs	72 obs	73 obs	74 obs	75 obs	76 obs	77 obs	78 obs	79 obs	80 obs
		12 Month	11 Month	10 Month	9 Month	8 Month	7 Month	6 Month	5 Month	4 Month	3 Month	2 Month	1 Month
Intervention Model	Month 70	23.45%											
	Month 71	9.40%	3.86%										
	Month 72	7.19%	3.49%	1.82%									
	Month 73	0.26%	9.83%	9.68%	8.77%								
	Month 74	1.58%	3.85%	4.42%	4.05%	1.76%							
	Month 75	11.30%	4.06%	3.04%	3.12%	6.43%	5.37%						
	Month 76	29.60%	17.33%	15.93%	15.86%	18.06%	17.59%	13.80%					
	Month 77	15.36%	8.63%	7.23%	7.09%	8.48%	8.34%	6.54%	1.63%				
	Month 78	6.31%	10.61%	11.82%	11.96%	11.06%	11.06%	11.91%	15.46%	14.69%			
	Month 79	31.72%	28.84%	27.07%	26.84%	27.97%	28.05%	27.24%	24.21%	24.64%	37.97%		
	Month 80	17.91%	18.52%	16.87%	16.65%	17.62%	17.73%	17.16%	15.23%	15.34%	21.11%	1.24%	
	Month 81	10.47%	3.69%	5.03%	5.21%	4.45%	4.35%	4.75%	6.00%	6.01%	3.54%	11.22%	12.01%
Seasonal Exponential Smoothing	Month 70	10.15%											
	Month 71	15.17%	20.73%										
	Month 72	20.21%	25.29%	13.22%									
	Month 73	25.97%	30.53%	19.71%	11.96%								
	Month 74	22.03%	26.79%	15.49%	7.39%	1.42%							
	Month 75	1.07%	6.18%	5.93%	14.61%	24.04%	22.99%						
	Month 76	10.51%	4.79%	18.37%	28.11%	38.69%	37.51%	20.41%					
	Month 77	1.97%	7.26%	5.29%	14.28%	24.06%	22.96%	7.17%	7.07%				
	Month 78	17.25%	21.59%	11.28%	3.89%	4.14%	3.24%	9.74%	21.43%	17.18%			
	Month 79	17.80%	11.54%	26.40%	37.04%	48.62%	47.32%	28.62%	11.77%	17.90%	35.27%		
	Month 80	7.00%	1.24%	14.90%	24.69%	35.34%	34.15%	16.95%	1.45%	7.09%	23.06%	2.55%	
	Month 81	24.46%	29.13%	18.04%	10.08%	1.43%	2.40%	16.37%	28.96%	24.38%	11.41%	28.07%	29.39%
ARIMA(1,1,1)	Month 70	6.42%											
	Month 71	8.92%	12.88%										
	Month 72	13.36%	16.33%	7.56%									
	Month 73	20.58%	22.90%	16.36%	11.37%								
	Month 74	15.61%	17.84%	11.67%	7.35%	1.46%							
	Month 75	8.33%	10.61%	4.31%	0.16%	7.56%	6.40%						
	Month 76	4.10%	1.59%	8.53%	12.95%	20.62%	19.56%	14.31%					
	Month 77	2.76%	5.05%	1.33%	5.33%	11.97%	11.10%	7.17%	2.52%				
	Month 78	19.20%	21.10%	15.83%	12.55%	7.26%	7.93%	10.78%	17.24%	15.71%			
	Month 79	17.63%	14.88%	22.55%	27.28%	34.82%	33.89%	30.04%	21.86%	23.64%	40.05%		
	Month 80	9.31%	6.76%	13.88%	18.27%	25.21%	24.37%	20.93%	13.91%	15.35%	27.49%	2.00%	
	Month 81	10.26%	12.36%	6.50%	2.90%	2.77%	2.09%	0.67%	6.20%	5.10%	3.56%	12.88%	14.02%
IMA(1,1)	Month 70	6.42%											
	Month 71	8.92%	18.89%										
	Month 72	13.36%	24.93%	13.02%									
	Month 73	20.58%	32.04%	21.23%	12.95%								
	Month 74	15.61%	28.20%	16.75%	7.97%	2.12%							
	Month 75	8.33%	22.20%	9.76%	0.23%	10.74%	9.05%						
	Month 76	4.10%	11.74%	2.40%	13.24%	25.71%	23.79%	16.42%					
	Month 77	2.76%	17.57%	4.34%	5.81%	17.48%	15.68%	8.78%	2.51%				
	Month 78	19.20%	31.52%	20.50%	12.05%	2.32%	3.82%	9.57%	18.97%	17.43%			
	Month 79	17.63%	0.28%	15.79%	28.13%	42.32%	40.14%	31.75%	18.03%	20.28%	38.61%		
	Month 80	9.31%	7.32%	7.65%	19.15%	32.37%	30.33%	22.51%	9.74%	11.83%	28.90%	5.16%	
	Month 81	10.26%	23.89%	11.58%	2.12%	8.76%	7.09%	0.65%	9.86%	8.14%	5.91%	13.63%	16.50%
SARIMA(0,1,1)(1,0,1)12	Month 70	10.16%											
	Month 71	1.43%	19.66%										
	Month 72	13.15%	25.09%	13.04%									
	Month 73	25.10%	31.49%	20.65%	11.57%								
	Month 74	24.56%	27.69%	16.27%	7.49%	0.67%							
	Month 75	22.02%	15.12%	3.05%	5.07%		13.36%	12.84%					
	Month 76	15.55%	4.44%	9.24%	20.59%	31.50%	30.97%	20.96%					
	Month 77	24.67%	13.05%	0.23%	9.54%	19.40%	18.87%	9.97%	4.20%				
	Month 78	40.17%	27.14%	16.55%	8.68%	0.78%	1.23%	8.89%	20.31%	17.75%			
	Month 79	16.67%	4.92%	20.34%	31.80%	42.95%	42.28%	31.01%	15.08%	18.80%	35.18%		
	Month 80	25.86%	3.56%	10.77%	21.07%	30.90%	30.25%	19.60%	5.71%	9.19%	23.40%	0.99%	

All Model Percentage Deviations

Appendix D

Monte Carlo Simulation Construction

Chapter 3 discussed the development of the parameters for the Monte Carlo Simulation. Below is a small portion of the airlift schedule from October FY2011. The table below shows which aircraft flew to what destination on what day. This schedule can be used to assign pallets to.

Table 16 Monte Carlo Simulation Construction

AirCraft	Type	Destination	Direct/Enroute	Day
B74720	CRAF	OAIX	Direct	1
B74720	CRAF	OAIX	Direct	2
B74740	CRAF	OAIX	Direct	3
B74720	CRAF	OAIX	Direct	3
B74720	CRAF	OAIX	Direct	3
B74720	CRAF	OAIX	Direct	4
B74720	CRAF	OAIX	Direct	4
MD011F	CRAF	OAIX	Direct	4
B74720	CRAF	OAKB	Direct	5
B74720	CRAF	OAKB	Direct	5
B74720	CRAF	OAIX	Direct	5
MD011F	CRAF	OAIX	Direct	5
B74720	CRAF	OAIX	Direct	6
B74740	CRAF	OAIX	Direct	7
B74720	CRAF	OAIX	Direct	7
MD011F	CRAF	OAIX	Direct	8
B74720	CRAF	OAIX	Direct	9
B74720	CRAF	OAIX	Direct	9
MD011F	CRAF	OAIX	Direct	10
B74710	CRAF	OAKB	Direct	10
MD011F	CRAF	OAIX	Direct	10
B74720	CRAF	OAIX	Direct	10
B74710	CRAF	OAIX	Direct	10
MD011F	CRAF	OAIX	Direct	11
MD011F	CRAF	OAIX	Direct	11
B74710	CRAF	OAKB	Direct	12
B74720	CRAF	OAIX	Direct	12
B74720	CRAF	OAIX	Direct	13

The right hand table shows a small portion of the pallets that arrive to Dover AFB, with their destination and their arrival date. The right hand table shows how each pallets' arrival date to Dover AFB is counted, the probability of occurrence is found, and then a discrete probability distribution is formed.

PLT_GROSS_WT	APOD_ICAO	ArrivalDate	DayCount	Day	Probability	CumProb
0.59	OAKN	1	72	1	4.52%	0.00%
5.01	OAIX	1	52	2	3.26%	4.52%
2.19	OAIX	1	26	3	1.63%	7.78%
2.94	OAIX	1	32	4	2.01%	9.41%
1.51	OAKN	1	70	5	4.39%	11.42%
1.40	OAKN	1	75	6	4.71%	15.81%
4.89	OAIX	1	89	7	5.58%	20.51%
2.50	OAIX	1	79	8	4.96%	26.10%
2.35	OAKN	1	43	9	2.70%	31.05%
1.97	OAIX	1	28	10	1.76%	33.75%
1.09	OAIX	1	12	11	0.75%	35.51%
1.94	OAIX	1	48	12	3.01%	36.26%
2.35	OAKB	1	53	13	3.32%	39.27%
1.64	OAIX	1	57	14	3.58%	42.60%
2.58	OAIX	1	92	15	5.77%	46.17%
2.57	OAIX	1	44	16	2.76%	51.94%
1.16	OAKN	1	37	17	2.32%	54.71%
2.84	OAIX	1	34	18	2.13%	57.03%
2.58	OAIX	1	53	19	3.32%	59.16%
2.23	OAIX	1	45	20	2.82%	62.48%
1.86	OAIX	1	59	21	3.70%	65.31%
4.31	OAIX	1	47	22	2.95%	69.01%
2.46	OAIX	1	43	23	2.70%	71.96%
2.55	OAKN	1	14	24	0.88%	74.65%
1.83	OAIX	1	39	25	2.45%	75.53%
2.16	OAIX	1	66	26	4.14%	77.98%
2.44	OAIX	1	59	27	3.70%	82.12%
4.45	OAKN	1	48	28	3.01%	85.82%
			68	29	4.27%	88.83%
			49	30	3.07%	93.10%
			61	31	3.83%	96.17%

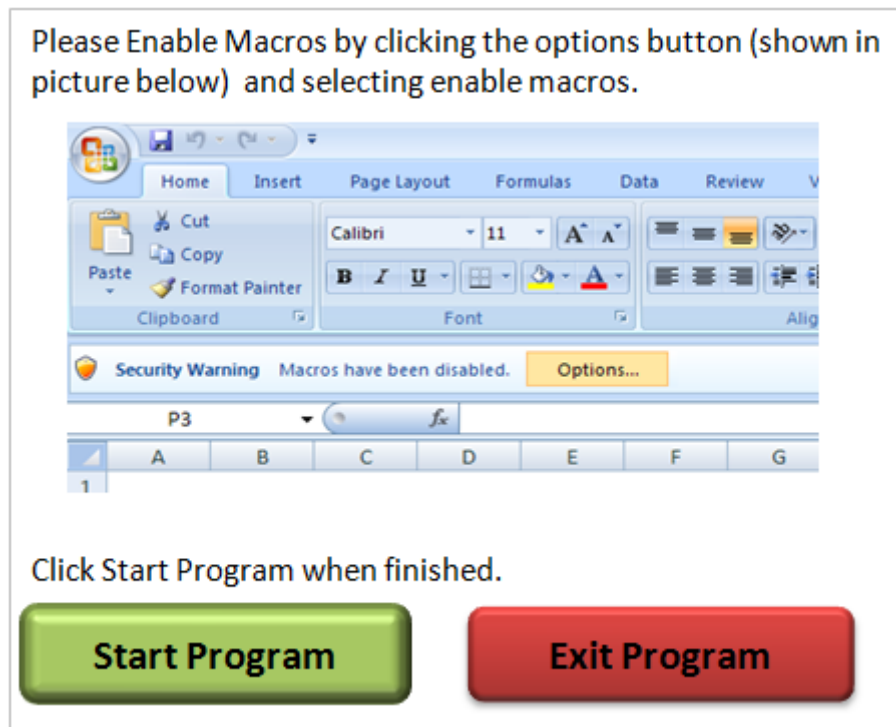
The table below shows how each pallets' destination is counted, the probability of occurrence is found, and then a discrete probability distribution is formed.

Destination	Direct/Enroute	Location #	Count	Probability	CumProb
OAIX	Direct	1	1103	69.20%	0.00%
OAKB	Direct	2	153	9.60%	69.20%
OAKN	Direct	3	338	21.20%	78.80%

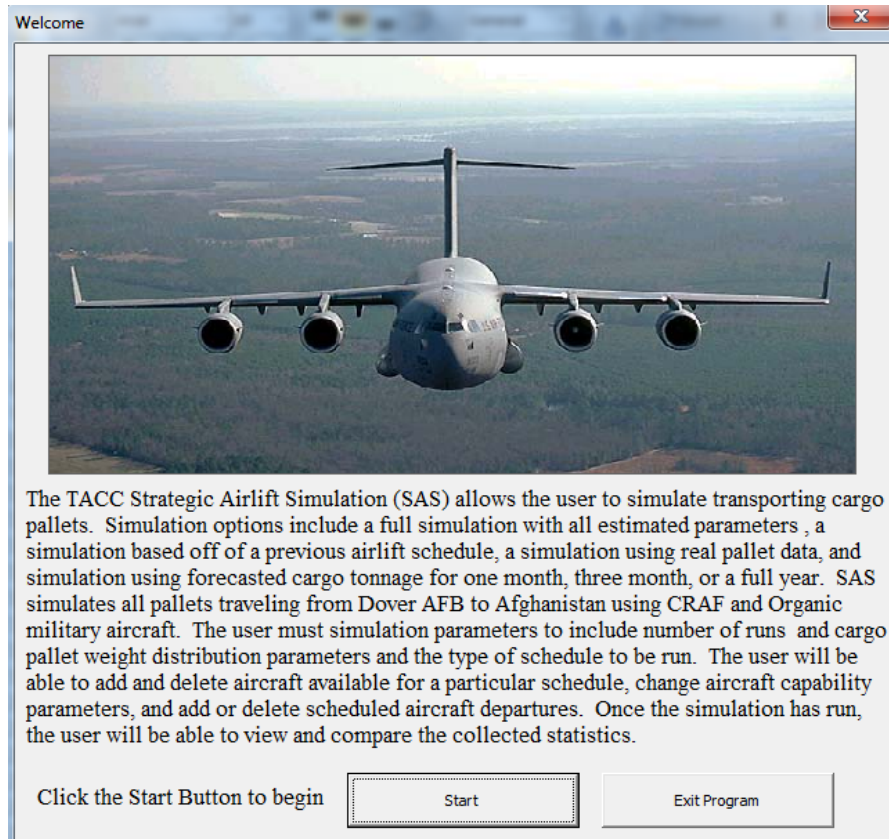
Appendix E

Decision Support System – Strategic Airlift Simulation Description

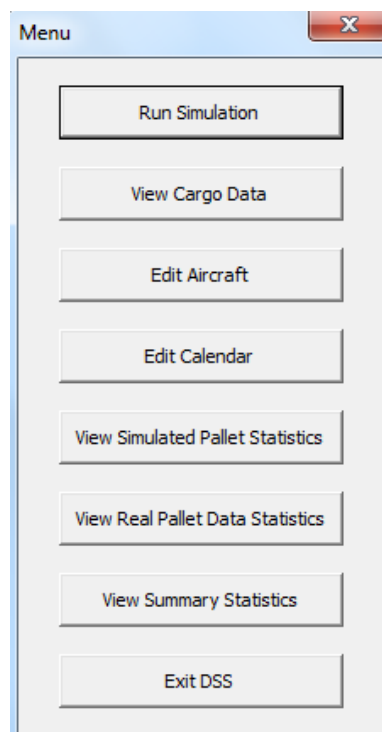
A decision support system is a computer based information system that can be used for management, operations, or for planning purposes. It uses data for processing or for analytical purposes to aid the decision maker in his or her decision-making process. A DSS was constructed with a graphical user interface (GUI) so that the sponsor at USTRANSCOM could perform the same actions as discussed throughout my research, but without assistance. The DSS requires a working knowledge of the CRAF scheduling program and a walk-through of the DSS. Screenshots and brief instructions will be laid out below as a brief tutorial for potential users.



Initial screen when opening TACCSAS



Welcome screen when starting TACCSAS



Menu appears when selecting “Start”

Simulation Parameters

Select Month
Please select the monthly schedule that you would like to simulate: **January**

Please Read: After selecting a month from the box above, the simulation parameters and distribution parameters are automatically generated based off of the real pallet data readily available for your use. These are only suggested values and are easily adjustable for your individual needs.

Simulation Choice
Please select whether you would like to run a Monte Carlo simulation or schedule real pallet data. You may also choose to run both and compare the results.

☒ **Monte Carlo Sim**
☐ **Real Pallet Schedule**
☐ **Run Both**
☐ **Run Full Year**
☐ **12 Month Forecast**
☐ **3 Month Forecast**
☐ **1 Month Forecast**

Cancel Rate for Organic Aircraft (Please enter as decimal): **0.1**

Simulation Parameters
Please set the simulation parameters below

Total Number of Iterations: **10**

Number of Pallets for Simulation: **4874**

Distribution Parameters
Please select the distribution of the weight of the pallets: **Normal**

Mean: **2.03876**

Standard Deviation: **1.25338**

Run **Reset** **Cancel**

Select “Run Simulation.” This screen provide seven options for simulation. The simulation choices include the “fixed buy” and the “expansion buy” forecast options. The recommended number of simulation iterations if 100. Upon opening, defaults will be provided within the selection.

Simulation Parameters

Select Month

Please select the monthly schedule that you would like to simulate

January

Please Read: After selecting a month from the box above, the simulation parameters and distribution parameters are automatically generated based off of the real pallet data readily available for your use. These are only suggested values and are easily adjustable for your individual needs.

Simulation Choice

Please select whether you would like to run a Monte Carlo simulation or schedule real pallet data. You may also choose to run both and compare the results.

☐ Monte Carlo Sim
☐ Real Pallet Schedule

☐ Run Both
☐ Run Full Year

☒ 12 Month Forecast
☐ 3 Month Forecast

☐ 1 Month Forecast

Cancel Rate for Organic Aircraft
(Please enter as decimal)

0.1

Simulation Parameters

Please set the simulation parameters below

Total Number of Iterations

10

Number of Pallets for Simulation

4874

Forecast Parameters

The forecast mean and standard deviation are found using a normal distribution taken from previous months data.

Please select the type of schedule you would like to simulate.

☐ All CRAF
☐ All Organic
☐ Mix
☒ Original

Run
Reset
Cancel

If the user selects a forecast simulation, forecast parameters will appear allowing for a variety of schedules to used in the simulation.

X

Add Aircraft to List

Please set the schedule values

Enter Aircraft Name

Select Aircraft Type

Enter Aircraft Tons

Enter Number of Pallets

Please enter minimum values as a percentage in decimal format (50% = .5)

Enter Minimum Aircraft Tons

Enter Minimum Number of Pallets

Add

Change Aircraft Parameters

Please set the schedule values

Select Aircraft

Select Aircraft Type

Change Aircraft Tons

Change Number of Pallets

Please enter minimum values as a percentage in decimal format (50% = .5)

Change Minimum Aircraft Tons

Change Minimum # of Pallets

Save

Delete Aircraft From List

Please set the schedule values

Pick Type of Aircraft

Delete

Return

Select “Edit Aircraft” from Menu. The user is allowed to change the ACL parameters for each type of aircraft. Users can also add new CRAF or Organic aircraft with capacity levels as well

Add Or Delete Dates

Select Month
Please select the month that you would like to schedule a flight in. [Dropdown]

Add Flight to Schedule
Please set the schedule values

Pick Type of Aircraft [Dropdown]
Pick Destination [Dropdown]
Pick Day of the Month [Dropdown]

Add

Delete Flight From Schedule
Please set the schedule values

Pick Type of Aircraft [Dropdown]
Pick Destination [Dropdown]
Pick Day of the Month [Dropdown]

Delete

Return

Select “Edit Calendar” from Menu. The user can choose a month and add CRAF or Organic flights to the schedule or remove them.

Run #	Avg Port Hold Of All Pallets	Avg Port Hold For Pallets Not Delivered	Pallets Not Shipped	Weight Not Shipped	Total Weight Generated	Total Weight Shipped
1	1.96	2.49	1480	3084.38	6558.89	3474.51
2	2.06	2.59	1554	3235.98	6558.89	3322.91
3	1.81	2.31	1537	3200.93	6558.89	3357.96
4	1.90	2.38	1560	3243.84	6558.89	3315.05
5	1.96	2.49	1480	3084.38	6558.89	3474.51
6	1.96	2.48	1492	3111.02	6558.89	3447.87
7	1.96	2.49	1480	3084.38	6558.89	3474.51
8	1.69	2.15	1505	3138.44	6558.89	3420.45
9	1.96	2.49	1480	3084.38	6558.89	3474.51
10	1.42	1.81	1533	3197.97	6558.89	3360.92

Select “View Simulated Pallet Statistics” or “View Real Pallet Statistics” from Menu. The user can view a large number of statistics provided for each run of the simulation. The

statistics are provided for pallets/tons airlifted and per individual aircraft type. The next two figures are also included in this selection.

Run #	CRAF Flown	CRAF Cancelled	Cost Of Schedule	Potential Total Cost	Cost Savings
1	30	15	\$ 15,300,000	\$ 20,700,000	\$ 5,400,000
2	30	15	\$ 15,300,000	\$ 20,700,000	\$ 5,400,000
3	30	15	\$ 15,300,000	\$ 20,700,000	\$ 5,400,000
4	30	15	\$ 15,300,000	\$ 20,700,000	\$ 5,400,000
5	30	15	\$ 15,300,000	\$ 20,700,000	\$ 5,400,000
6	30	15	\$ 15,300,000	\$ 20,700,000	\$ 5,400,000
7	30	15	\$ 15,300,000	\$ 20,700,000	\$ 5,400,000
8	30	15	\$ 15,300,000	\$ 20,700,000	\$ 5,400,000
9	30	15	\$ 15,300,000	\$ 20,700,000	\$ 5,400,000
10	30	15	\$ 15,300,000	\$ 20,700,000	\$ 5,400,000

Run #	Aircraft ID	# of Missions	Tons Transferred	Tons Per Mission	Tonnage Utilization	Pallets Per Mission	Pallet Utilization	Potential Pallet Positions	Actual Pallets Shipped	Total Pallet Utilization	Avg Pallet Weight
1	B74720	21	2882.24	137.25	1.23	72.67	1.08	1407.00	1526.00	1.08	1.89
2	B74720	21	2882.24	137.25	1.23	72.67	1.08	1407.00	1526.00	1.08	1.89
3	B74720	21	2882.24	137.25	1.23	72.67	1.08	1407.00	1526.00	1.08	1.89
4	B74720	21	2882.24	137.25	1.23	72.67	1.08	1407.00	1526.00	1.08	1.89
5	B74720	21	2882.24	137.25	1.23	72.67	1.08	1407.00	1526.00	1.08	1.89
6	B74720	21	2882.24	137.25	1.23	72.67	1.08	1407.00	1526.00	1.08	1.89
7	B74720	21	2882.24	137.25	1.23	72.67	1.08	1407.00	1526.00	1.08	1.89
8	B74720	21	2882.24	137.25	1.23	72.67	1.08	1407.00	1526.00	1.08	1.89
9	B74720	21	2882.24	137.25	1.23	72.67	1.08	1407.00	1526.00	1.08	1.89
10	B74720	21	2882.24	137.25	1.23	72.67	1.08	1407.00	1526.00	1.08	1.89

Appendix F

Contact Information

If anyone is interested in the code that was used in Excel to perform all of the operations and analysis mentioned earlier, please refer to the contact information below.

Dr. Jeffery Weir
Jeffery.weir@afit.edu

Taylor Leonard, Capt. (USAF)
Taylor.Leonard.1@us.af.mil

Vita

Captain Taylor J. Leonard graduated from Gig Harbor High School in Gig Harbor, Washington. He entered the United States Air Force Academy (USAFA) in Colorado Springs, Colorado where he graduated with a Bachelor of Science degree in Operations Research and commissioned in 2008.

His first assignment was at Eglin AFB as a Command and Control Test Analyst in the 46th Test Squadron (TS). In October 2010, he served as Deputy Director of the Datalink Test Facility at the 46TS. In September 2011, he entered the Graduate School of Engineering and Management, Air Force Institute of Technology. Upon graduation, he will be assigned as a faculty member of the Department of Mathematical Sciences at USAFA.

REPORT DOCUMENTATION PAGE				Form Approved OMB No. 074-0188	
<p>The public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of the collection of information, including suggestions for reducing this burden to Department of Defense, Washington Headquarters Services, Directorate for Information Operations and Reports (0704-0188), 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.</p> <p>PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ADDRESS.</p>					
1. REPORT DATE (DD-MM-YYYY) 21-03-2013		2. REPORT TYPE Master's Thesis		3. DATES COVERED (From – To) Oct 2011 – Mar 2013	
4. TITLE AND SUBTITLE Operational Planning of Channel Airlift Missions Using Forecasted Demand				5a. CONTRACT NUMBER	
				5b. GRANT NUMBER	
				5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S) Leonard, Taylor J., Capt, USAF				5d. PROJECT NUMBER JON 13S141	
				5e. TASK NUMBER	
				5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S) Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/EN) 2950 Hobson Street WPAFB OH 45433-7765				8. PERFORMING ORGANIZATION REPORT NUMBER AFIT-ENS-13-M-09	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Amy Pappas USTRANSCOM/TCAC 508 Scott Dr. Scott AFB, IL 62225 (618) 220-7758, (DSN 770-7758) and amy.pappas@ustranscom.mil				10. SPONSOR/MONITOR'S ACRONYM(S) USTRANSCOM/TCAC	
				11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION/AVAILABILITY STATEMENT Distribution Statement A Approved For Public Release; Distribution Unlimited					
13. SUPPLEMENTARY NOTES This material is declared a work of the U.S. Government and is not subject to copyright protection in the United States.					
9. ABSTRACT Past research proposed that it is possible to forecast cargo demand using time series models and that there exists potential cost savings in the way that Civilian Reserve Air Fleet (CRAF) is used for cargo airlift. United States Transportation Command (USTRANSCOM) performs annual "fixed-buys" of CRAF to support airlift needs. Forecasted cargo demand would allow for reasonably accurate cargo projections vs. the current expected value estimation. Accurate forecasting allows for greater "fixed-buys," further incentivizing CRAF airlines as well as reducing the number of additional aircraft purchases during the quarterly and monthly buys. Multiple forecasting models are constructed and the results compared. A Monte Carlo simulation using a discrete pallet destinations distribution and a discrete pallet port arrival date distribution (based on historical data) outputs a month of projected pallet weights (with date and destination) that are equivalent to the forecasted cargo amount. The simulated pallets are then used in a heuristic cargo loading algorithm. The loading algorithm places cargo onto available aircraft (based on real schedules) given the date and the destination and outputs statistics based on the aircraft ton and pallet utilization as well as number of aircraft types used and the total cost of the projected airlift schedule. A technical approach to the operational planning of cargo airlift could provide significant cost savings or could provide an alternative planning approach changing the future of USTRANSCOM operations.					
15. SUBJECT TERMS Cargo Forecasting, Aircraft Scheduling, Cargo Generation, Civil Reserve Air Fleet					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Dr. Jeffery Weir
U	U	U	UU	103	19b. TELEPHONE NUMBER (Include area code) (937) 255-3636

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39-18